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sweet swiss energy research for the energy transition

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Summary

The objective of this work is to model spatially-explicit scenarios of growth in solar PV, heat pumps, and battery electric vehicles in Switzerland from 2020 to 2050, using statistical and optimization models. First, in SWEET SURE, these scenarios would be later used to test electricity and gas grids and the integrated Swiss energy system as a whole on sustainability and resilience in shock events. This work also acts as a reference to assess the realism or feasibility of technical scenarios from other SURE models. Second, such scenarios are useful to support decision-making in Switzerland on transition policies and local infrastructure investments by better understanding the dynamics behind the technology uptake for accelerating the process.

This work presents the acquired results as three journal paper manuscripts: (i) a published manuscript on spatially-explicit probabilistic projections of solar PV, heat pumps, and battery electric vehicles in Switzerland until 2050; (ii) an accepted manuscript on comparing statistical and optimization models for generating spatially-explicit Swiss projections of solar PV installations in the short run, and (iii) a manuscript on statistical analysis of spatial patterns in residential heat pump adoption in Switzerland. Overall, statistical models are found to be better fit for the purpose for modeling short-term as well as long-term spatial projections of these granular technologies. This work results in spatially-explicit projections of growth in solar PV, heat pumps, and battery electric vehicles by 2050, including most likely and more disruptive, yet less likely developments. If the current trends continue, Switzerland is on track to only have 12.5 GW of solar PV, 0.6 million buildings with heat pumps, and 1.4 million battery electric vehicles by 2050, and hence needs to become more ambitious to reach its net-zero emissions target with higher certainty by 2050. We plan to update these projections every year using the latest available data and provide them with free access on Zenodo.

Our work also demonstrates the need to develop local strategies and policies within current and further work in SWEET SURE by integrating spatial heterogeneity and regional specificities to identify additional potentials where technologies are likely to be installed. The regional specificities include examples, such as that solar PV is more installed in areas with comparatively high technical potentials, population density, and household size. In contrast, residential heat pumps are installed more in sparsely populated areas where the shares of agricultural area and detached houses are higher, while economic factors, like income and electricity price, show only limited impact.

Zusammenfassung

Ziel dieser Arbeit ist die Modellierung von räumlich expliziten Szenarien für den Ausbau von Photovoltaik, Wärmepumpen und batteriebetriebenen Elektrofahrzeugen in der Schweiz von 2020 bis 2050 unter Verwendung von statistischen Modellen und Optimierungsmodellen. Diese Szenarien werden später in SWEET SURE verwendet, um die Strom- und Gasnetze und das integrierte Schweizer Energiesystem als Ganzes auf Nachhaltigkeit und Widerstandsfähigkeit gegenüber Schockereignissen zu testen. Diese Arbeit dient auch als Referenz, um Realismus oder Machbarkeit von technischen Szenarien aus anderen Modellen in SURE zu bewerten. Zweitens sind solche Szenarien nützlich, um die Entscheidungsfindung in der Schweiz in Bezug auf Politikkurs und lokale Infrastrukturinvestitionen zu unterstützen, indem die Dynamik zur Beschleunigung der Technologieeinführung besser verstanden wird.

Diese Arbeit präsentiert die erzielten Ergebnisse in Form von drei Manuskripten: (i) ein publiziertes Manuskript über räumlich explizite probabilistische Projektionen von Photovoltaik, Wärmepumpen und batteriebetriebenen Elektrofahrzeugen in der Schweiz bis 2050; (ii) ein angenommenes Manuskript über den Vergleich von statistischen Modellen und Optimierungsmodellen zur Erstellung von räumlich expliziten Projektionen von Photovoltaik in der Schweiz auf kurze Sicht und (iii) ein Manuskript über die

statistische Analyse von räumlichen Mustern bei der Installation von Wärmepumpen in der Schweiz. Statistische Modelle haben sich insgesamt als besser geeignet erwiesen, um sowohl kurzfristige als auch langfristige räumliche Projektionen für diese granularen Technologien zu modellieren. Insgesamt führt das Ergebnis dieser Arbeit zu räumlich expliziten Projektionen für den Ausbau von Photovoltaik, Wärmepumpen und batteriebetriebenen Elektrofahrzeugen bis 2050, einschliesslich der wahrscheinlichsten und der eher disruptiven, aber weniger wahrscheinlichen Entwicklungen. Wenn sich die aktuellen Trends fortsetzen, wird die Schweiz bis 2050 nur 12,5 GW Photovoltaik, 0,6 Millionen Gebäude mit Wärmepumpen und 1,4 Millionen batteriebetriebene Elektrofahrzeuge haben und muss daher ambitionierter werden, um ihr Ziel von Netto-Null Emissionen bis 2050 mit höherer Wahrscheinlichkeit zu erreichen. Wir planen diese Projektionen jedes Jahr anhand der neuesten verfügbaren Daten zu aktualisieren und machen sie auf Zenodo frei zugänglich.

Unsere Arbeit zeigt auch die Notwendigkeit im Rahmen der laufenden und weiteren Arbeiten von SWEET SURE lokale Strategien und Politiken zu entwickeln, in denen räumliche Ungleichheiten und regionale Besonderheiten berücksichtigt werden, um zusätzliche Potenziale zu ermitteln, wo Technologien wahrscheinlich installiert werden. Zu den regionalen Besonderheiten gehören beispielsweise die Tatsache, dass PV-Anlagen eher in Gebieten mit vergleichsweise hohem technischen Potenzial, hoher Bevölkerungsdichte und Haushaltsgrösse installiert werden. Im Gegensatz dazu werden Wärmepumpen für Wohngebäude eher in dünn besiedelten Gebieten installiert, in denen der Anteil an landwirtschaftlichen Flächen und Einfamilienhäusern höher ist, während wirtschaftliche Faktoren wie Einkommen und Strompreise nur begrenzte Auswirkungen haben.

Résumé

L'objectif de ce travail est de modéliser des scénarios spatialement explicites de croissance de l'énergie solaire photovoltaïque, des pompes à chaleur et des véhicules électriques à batterie en Suisse entre 2020 et 2050, en utilisant des modèles statistiques et d'optimisation. Dans un premier temps, dans le cadre de SWEET SURE, ces scénarios seront ensuite utilisés pour tester la durabilité et la résilience des réseaux d'électricité et de gaz et du système énergétique suisse intégré dans son ensemble en cas de chocs. Ce travail sert également de référence pour évaluer le réalisme ou la faisabilité des scénarios techniques d'autres modèles SURE. Deuxièmement, ces scénarios sont utiles pour soutenir la prise de décision en Suisse sur les politiques de transition et les investissements dans les infrastructures locales en comprenant mieux la dynamique derrière l'adoption de la technologie pour accélérer le processus.

Ce travail présente les résultats acquis sous la forme de trois manuscrits d'articles de revues : (i) un manuscrit publié sur les projections probabilistes spatialement explicites de l'énergie solaire photovoltaïque, des pompes à chaleur et des véhicules électriques à batterie en Suisse jusqu'en 2050 ; (ii) un manuscrit accepté sur la comparaison des modèles statistiques et d'optimisation pour générer des projections suisses spatialement explicites des installations solaires photovoltaïques à court terme, et (iii) un manuscrit sur l'analyse statistique des modèles spatiaux de l'adoption des pompes à chaleur résidentielles en Suisse. Dans l'ensemble, les modèles statistiques s'avèrent mieux adaptés à la modélisation des projections spatiales à court terme et à long terme de ces technologies granulaires. Ces travaux aboutissent à des projections spatiales explicites de la croissance de l'énergie solaire photovoltaïque, des pompes à chaleur et des véhicules électriques à batterie d'ici à 2050, y compris les développements les plus probables et les plus perturbateurs, mais aussi les moins probables. Si les tendances actuelles se poursuivent, la Suisse ne disposera que de 12,5 GW d'énergie solaire photovoltaïque, de 0,6 million de bâtiments équipés de pompes à chaleur et de 1,4 million de véhicules électriques à batterie d'ici 2050, et devra donc se montrer plus ambitieuse pour atteindre avec plus de certitude son objectif d'émissions nettes nulles d'ici 2050. Nous prévoyons de mettre à jour ces projections chaque année en utilisant les dernières données disponibles et de les fournir en accès libre sur Zenodo.

Notre travail démontre également la nécessité de développer des stratégies et des politiques locales dans le cadre des travaux actuels et futurs de SWEET SURE en intégrant l'hétérogénéité spatiale et les spécificités régionales afin d'identifier des potentiels supplémentaires où les technologies sont susceptibles d'être installées. Les spécificités régionales sont illustrées par des exemples tels que l'installation de panneaux solaires photovoltaïques dans des zones où le potentiel technique, la densité de population et la taille des ménages sont relativement élevés. En revanche, les pompes à chaleur résidentielles sont davantage installées dans les régions à faible densité de population, où la part des zones agricoles et des maisons individuelles est plus importante, tandis que les facteurs économiques, tels que le revenu et le prix de l'électricité, n'ont qu'un impact limité.

Riassunto

Questo lavoro si pone l’obiettivo di modellare scenari spazialmente espliciti di crescita del solare fotovoltaico, delle pompe di calore e dei veicoli elettrici (a batteria) in Svizzera dal 2020 al 2050, utilizzando modelli statistici e di ottimizzazione. Questi scenari saranno in primo luogo adoperati in SWEET SURE per testare la sostenibilità e la resilienza delle reti elettriche e del gas, e del sistema energetico nazionale nel suo complesso in caso di “shock”. Inoltre, questo primo lavoro funge anche da riferimento per valutare la realisticità o la fattibilità tecnica degli scenari di altri modelli SURE. In secondo luogo, tali scenari sono utili per supportare il processo decisionale sulle politiche di transizione e sugli investimenti locali per le infrastrutture in Svizzera. Comprendere meglio le dinamiche dietro l'adozione delle nuove tecnologie può contribuire ad accelerarne il processo.

I risultati di questo lavoro saranno presentati mediante tre pubblicazioni scientifiche (in fase di elaborazione): (i) un articolo sulle proiezioni probabilistiche spaziali del solare fotovoltaico, delle pompe di calore e dei veicoli elettrici a batteria in Svizzera fino al 2050; (ii) un articolo sul confronto tra modelli statistici e di ottimizzazione per la generazione di proiezioni spaziali delle installazioni del solare fotovoltaico in Svizzera nel breve periodo e (iii) un articolo sull'analisi statistica dei pattern di adozione delle pompe di calore residenziali in Svizzera. Nel complesso, i modelli statistici si sono rivelati più idonei per la modellazione di proiezioni spaziali a breve e a lungo termine di queste tecnologie modulari. Questo lavoro fornisce proiezioni spazialmente esplicite della crescita del solare fotovoltaico, delle pompe di calore e dei veicoli elettrici a batteria entro il 2050, includendo gli sviluppi più probabili e quelli più dirompenti, ma anche quelli meno probabili. Con gli andamenti attuali, in Svizzera si prevedono solo 12.5 GW di solare fotovoltaico, 0.6 milioni di edifici con pompe di calore e 1.4 milioni di veicoli elettrici a batteria entro il 2050. È dunque necessario adottare misure più ambiziose per raggiungere con maggiore certezza l'obiettivo di zero emissioni nette entro il 2050. Aggiorneremo queste proiezioni ogni anno utilizzando i nuovi dati disponibili e forniremo loro un libero accesso su Zenodo.

Il nostro lavoro dimostra anche la necessità di sviluppare strategie e politiche locali nell’attuale e futuro lavoro di SWEET SURE. Di particolare interesse è l’integrazione dell'eterogeneità spaziale e delle specificità regionali per identificare ulteriori potenziali in cui le tecnologie saranno installate con maggiore probabilità. Le specificità regionali hanno delle caratteristiche comuni, come il fatto che il solare fotovoltaico è maggiormente installato nelle aree con le più alte dimensioni delle famiglie, densità della popolazione e con i più alti potenziali tecnici. Al contrario, le pompe di calore residenziali sono installate maggiormente nelle aree scarsamente popolate, dove le quote di superficie agricola e di case unifamiliari sono più elevate, mentre i fattori economici, come il reddito e il prezzo dell'elettricità, hanno un impatto limitato.

1 Introduction

The objective of this work is to model spatially-explicit scenarios of growth in solar PV and heat pumps in Switzerland from 2020 to 2050, using statistical and optimization approaches. The aim is to include scenarios of potentially disruptive growth in PV and heat pumps too for SURE resilience analysis later on. This work presents the acquired results as three journal paper manuscripts (chapters).

First, in Chapter 2, we develop a new method to create spatially-explicit probabilistic projections of granular technology diffusion based on historical time series data. Probabilistic projections help us distinguish between the most likely projections (e.g. median estimates) and the less likely, disruptive projections (e.g. 95% confidence interval). We apply this method on the cases of solar PV, heat pumps, and battery electric vehicles at a municipality level throughout Switzerland. We focus on the time horizons of 2000 – 2021 for testing the modeling approach and on 2021 – 2050 for policy analysis. Based on our probabilistic projections, we find that, if the current trends continue, Switzerland will most likely only have 12.5 GW of solar PV, 0.6 million buildings with heat pumps and 1.4 million battery electric vehicles by 2050. Thus, the country has to become more ambitious to reach its net-zero emissions target with higher certainty by 2050.

In Chapter 3, we focus on methodologies for modeling the uptake of solar PV. We project and compare PV installations at a level of 143 districts in Switzerland, using simple extrapolation method (as a benchmark of the common practice today), a multiple linear regression model, two spatial regression models, and a spatially-explicit EXPANSE optimization model with various features to account for policy. The performance of different models is evaluated retrospectively in 2012 – 2020, using multiple accuracy indicators. The results show that statistical regression models, which account for socio-demographic and techno-economic characteristics as predictors of future PV growth, overall perform better than extrapolation or optimization. We thus conclude that statistical models are preferred for projecting future PV installations at a sub-national scale.

In Chapter 4, we further investigate spatial patterns in the distribution of 319’341 residential buildings with heat pumps in Switzerland in 2021. Using stepwise regression and spatial statistical analysis, we show that residential heat pumps primarily have a higher diffusion level in sparsely populated areas where the shares of agricultural area and detached houses are higher. Economic factors, like income and electricity price, have a limited impact on residential heat pump diffusion in Switzerland, except for unemployment rate that has a negative impact. Some Swiss cantons have a distinctly higher or lower residential heat pump diffusion level than others, a phenomenon possibly induced by cantonal policies.

Overall, this work presents spatially-explicit projections of growth in solar PV, heat pumps, and battery electric vehicles by 2050, including most likely and more disruptive, yet less likely developments. Using statistical models, this work also reveals the role of various socio-demographic and techno-economic predictors of spatial adoption of solar PV and heat pumps in Switzerland, including some insights on the role of policy, where data allows. Statistical models are overall found to be better fit for purpose for modeling short-term as well as long-term spatial projections of these granular technologies.

2 Spatially-explicit probabilistic projections of granular energy technology diffusion at subnational level

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2.1 Abstract

Projections of granular energy technology diffusion can support decision-making on climate mitigation policies and infrastructure investments. However, such projections often do not account for uncertainties and have low spatial resolution. S-curve models of technology diffusion are widely used to project future installations, but the results of the different models can vary significantly. We propose a method to create spatially-explicit probabilistic projections of granular energy technology diffusion based on historical time series data and on testing how various projection models perform in terms of accuracy and uncertainty to inform the choice of models. As a case study, we investigate the growth of solar photovoltaics, heat pumps, and battery electric vehicles at a municipality level throughout Switzerland in 2000 – 2021 (testing) and until 2050 (projections). Consistently for all S-curve models and technologies, we find that the medians of the probabilistic projections anticipate the diffusion of the technologies more accurately than the respective deterministic projections. While accuracy and probabilistic density intervals of the models vary across technologies, municipalities, and years, Bertalanffy and two versions of the generalized Richard models estimate the future diffusion with higher accuracy and sharpness than the logistic, Gompertz, and Bass models. The results also highlight that all models come with tradeoffs and eventually a combination of models with weights is needed. Based on these weighted probabilistic projections, we show that, given current dynamics of diffusion in solar photovoltaics, heat pumps, and battery electric vehicles in Switzerland, the net-zero emissions target would be missed by 2050 with high certainty.

2.2 Introduction

Energy system models are widely used to quantify pathways that reach certain environmental or technological goals of the energy transition (1, 2). While such models set normative targets, these models cannot inform about the realistic pathways (3), especially for new granular technologies like solar photovoltaics (PV), heat pumps, or Battery Electric Vehicles (BEV). Hence, realistic projections of energy technology diffusion would be useful to support decision-making on transition policies and infrastructure investments. However, such projections often have three major limitations: they are deterministic and do not account for uncertainties (4–6), they have a low spatial resolution (7, 8), and they rely on a single model with numerous input assumptions (9–11). The quantification of uncertainties is particularly relevant when technology diffusion is non-linear (12) or the projections directly assist decision-making (13, 14). Recent studies make first efforts in adopting probabilistic approaches to account for uncertainties in technology projections at national or international level (10, 15, 16), often with Monte Carlo simulations with a single model (7, 17, 18). Expert elicitations can also provide estimates of uncertainties, but literature shows that elicitations can still notably deviate from reality (12, 19, 20) and that data-driven methods project future developments more accurately (16, 21).

To project future technology diffusion, studies commonly fit S-curve diffusion models to historical data (4, 5, 22). S-curves combine the influence of economic, social and technological factors on technology diffusion over time (8, 23, 24) and show similar growth behavior as seen in history (7, 25, 26). Standard S-curves describe initial exponential growth that increases up to an inflection point after which the growth eventually slows down until the curve saturates at its maximum. Standard S-curves are uniform as they have one inflection point. However, real diffusion can have multiple inflection points, for example, due to changes in technology policy, that can be modeled with Bi-S-curves or curves of higher order (27–29). While most popular S-curve models are the uniform versions of logistic, Gompertz and Bass models, there are plentiful alternative parametrizations of S-curves (23, 30, 31). However, the projections of different models can vary significantly (23, 31) and are sensitive to the choice of model parameters (24, 26, 32). Still, most studies rely on one or two models (5, 7, 8) without examining the suitability of the models to the given data, let alone the quality of the projections.

We propose a method to create spatially-explicit probabilistic projections of the diffusion of granular energy technologies based on historical time series data and on testing which projection models perform best in terms of accuracy and uncertainty to inform the choice of the models. Using historical time series of technology diffusion as an input minimizes the need for alternative input variables that can be scarce at a local level. Historical times series can capture long-term trends by implicitly carrying relevant economic, social, or technological information related to the diffusion of a technology (23, 33). As a case study, we investigate the growth of three granular energy technologies, solar PV, heat pumps, and BEV, at municipality level throughout Switzerland historically in 2000 – 2021 (testing) and until 2050 (projection). Solar PV, heat pumps, and BEV are key transition technologies to reduce Swiss greenhouse gas emissions (34–36). We analyze solar PV in installed capacity in three variables: absolute, per 100 inhabitants, and per technical potential in kW. We analyze numbers of heat pumps and BEV also in three variables: absolute, per 100 inhabitants, and per total number of existing buildings and civil passenger cars, respectively (see Section 2.5).

To create the probabilistic projections, we use a four-step process that we repeat for each of 2’148 Swiss municipalities (Figure 2-1; see 2.5*).* First, we fit twelve different S-curve models on the historical time series data of each technology’s diffusion. Second, we combine the curves of historically similar municipalities to form a probabilistic density interval for each S-curve model. Third, we evaluate each probabilistic projection using iterative hindcasting with out-of-sample testing and performance metrics. The metrics include, for instance, Mean Absolute Percentage Error (MAPE) and sharpness and calibration that sum to the Weighted Interval Score (WIS) (37). The WIS approximates the Continuous Ranked Probability Score (CRPS) here. Finally, we convert the mean WIS of each projection model into weights that we use to combine the models to create a final probabilistic projection for each municipality. Altogether, the uncertainty in the projections comes from both different S-curve models and municipalities. To create a national projection, we sum the quantiles of all Swiss municipalities, e.g., the national median means that all municipalities follow their median simultaneously. We then compare the national projection with published normative scenarios of the Swiss energy system with net-zero greenhouse gas emissions by 2050.

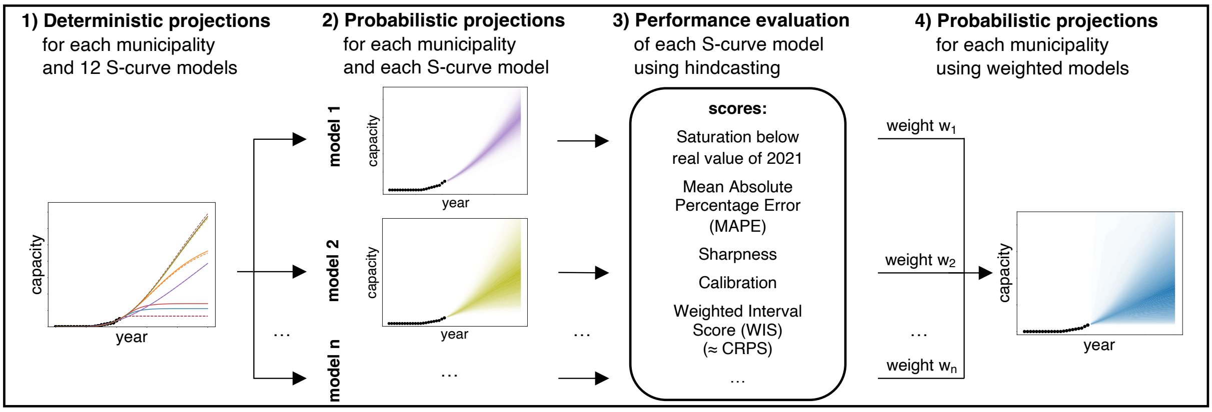

Figure 2-1. Methods flow chart for creating spatially-explicit probabilistic projections of granular energy technology diffusion. Section 5.1.1.1 shows each step and the underlying assumptions in detail. CRPS: Continuous Ranked Probability Score.

2.3 Results

Probabilistic vs. deterministic projections

Consistently for all S-curve models and technologies, we find in hindcasting that the medians of the probabilistic projections are more accurate than the respective deterministic projections (Figure 2-2). The average MAPE over all municipalities and hindcasting iterations is consistently lower for the median of the probabilistic projections than for the deterministic projections and lowers even further with an increasing number of samples used in the creation of the probabilistic projections (Appendix 5.1.1.2). For both type of projections, the magnitude of the MAPE depends on the technology and its historical time series. The projections of installed capacities of solar PV deviate more from the real diffusion than the respective projections of buildings with a heat pump and registered BEV. The results are comparable to the ones for the diffusion per 100 inhabitants and per unit of technical potential (Appendix 5.1.2.1). The difference in accuracy between the results of deterministic and probabilistic projections partially derives from the fact that the deterministic projections tend to underestimate and saturate at a lower level than the real diffusion (Figure 2-2). As a comparison of solar PV, heat pumps and BEV points out, the behavior of low saturation appears both in projections for the near future and for the comparatively distant future of up to ten years.

model	share of curves saturating below real value of 2021	MAPE (point projection)	MAPE (probabilistic proj.)	sharpness / WIS	calibration / WIS	WIS	weight	share of curves saturating below real value of 2021	MAPE (point projection)	MAPE (probabilistic proj.)	sharpness / WIS	calibration / WIS	WIS	weight	share of curves saturating below real value of 2021	MAPE (point projection)	MAPE (probabilistic proj.)	sharpness / WIS	calibration / WIS	WIS	weight
Bass	0.62	3.24	0.91	0.28	0.72	3.12	5.47	0.50	0.23	0.12	0.28	0.72	0.36	8.85	0.25	0.85	0.34	0.39	0.61	1.09	11.54
Bertalanffy	0.04	0.43	0.37	0.07	0.93	1.49	17.37	0.25	0.16	0.10	0.33	0.67	0.31	14.58	0.23	0.52	0.33	0.22	0.78	1.07	16.20
Gompertz	0.54	1.84	0.65	0.32	0.68	2.08	8.72	0.39	0.19	0.11	0.34	0.66	0.33	11.31	0.27	2.83	0.33	0.59	0.41	1.78	5.68
Logistic	0.63	3.47	0.89	0.27	0.73	3.10	5.64	0.52	0.24	0.13	0.28	0.72	0.36	8.87	0.28	0.96	0.33	0.35	0.65	1.08	11.47
Richards-4p	0.09	0.90	0.57	0.13	0.87	2.04	8.56	0.27	0.18	0.10	0.35	0.65	0.31	14.21	0.24	1.09	0.33	0.30	0.70	1.13	11.56
Richards-5p	0.11	0.89	0.55	0.14	0.86	1.98	8.73	0.27	0.18	0.10	0.35	0.65	0.31	14.10	0.21	1.06	0.33	0.33	0.67	1.13	11.45
Bi-Bass	0.48	2.99	0.90	0.36	0.64	3.08	4.52	0.54	0.29	0.13	0.42	0.58	0.37	7.40	0.23	1.89	0.34	0.70	0.30	1.45	6.94
Bi-Bertalanffy	0.04	0.43	0.37	0.06	0.94	1.49	17.26	0.23	0.18	0.10	1.00	0.00	> 10	1.32	0.13	0.56	0.30	1.00	0.00	> 10	1.61
Bi-Gompertz	0.35	4.46	0.64	0.69	0.31	3.03	5.29	0.28	0.59	0.10	0.61	0.39	0.39	7.72	0.17	5.05	0.32	1.00	0.00	2.36	3.42
Bi-Logistic	0.42	6.47	0.95	0.67	0.33	6.30	1.56	0.39	0.74	0.11	1.00	0.00	> 10	3.70	0.24	0.95	0.33	0.44	0.56	1.08	11.09
Bi-Richards-4p	0.11	1.04	0.57	0.17	0.83	1.98	8.22	0.28	0.23	0.10	1.00	0.00	> 10	6.90	0.09	0.97	0.30	1.00	0.00	> 10	2.35
Bi-Richards-5p	0.05	1.06	0.58	0.16	0.84	2.03	8.52	0.30	0.23	0.10	1.00	0.00	> 10	1.05	0.11	1.03	0.31	1.00	0.00	> 10	6.69
	Solar PV capacity							Buildings with a heat pump							Registered BEV						

Figure 2-2. Heat map with weights and scores of model performance from hindcasting for solar PV capacity, heat pumps and Battery Electric Vehicles (BEV). For each column, colors rank each score from highest (red) to lowest (blue) and vice versa for the weight. The shown values are means over all municipalities and hindcasting iterations with one- to ten-year ahead projections for solar PV and heat pumps, and one- to four-year ahead projections for BEV. For temporal evolutions, see Figures 5-8 – 5-12 in Appendix 5.1. The Mean Absolute Percentage Error (MAPE) of a probabilistic projection quantifies the error between the median value of the projection and the real value. To enhance comparability as some Bi-S-curves have scores that are multiple orders higher than 10, the highest 2% of MAPE scores of the deterministic projections are removed for all models before taking the mean. For BEV, the highest 2% of scores are also removed for Weighted Interval Scores (WIS) that approximate the continuous ranked probability score. Models that still have mean scores above 10 are indicated.

When comparing the S-curve models, the hindcasting exercise reveals substantial differences in their performance in projecting future technology diffusion. While the probabilistic density intervals vary across technologies, municipalities, and years, Bertalanffy and both generalized Richards models show on average lower MAPE and WIS than the ones of logistic, Gompertz, and Bass models (Figure 2-2). Therefore, the estimated median values are both closer to the real diffusion of solar PV, heat pumps, and BEV and the probabilistic density intervals cover the distribution of the real diffusion more precisely. Consequently, the models of Bertalanffy and Richards receive higher weights for the final probabilistic projections in most cases (Figure 2-2). However, the performance and thus the distribution of weights depends on the municipality and its historical time series of technology diffusion. For some municipalities, also the overall low performing models of logistic, Gompertz, and Bass receive comparatively high weights of up to 55 (Appendix 5.1.2.2). Note that for solar PV, the projections of the Bi-S-curves of Bertalanffy and Richards show the same shape as the ones of their corresponding uniform S-curves in most municipalities, resulting in almost identical scores. For heat pumps and BEV, the Bi-S-curves mostly have different shapes and lower performance than the uniform models.

Beyond comparing the performance in terms of MAPE and WIS, alternative characteristics can play a role in choosing models for the projections. These characteristics can include the complexity of a model, the development of the historical time series of a diffusion, or sharpness and distribution of the probabilistic density interval. The complexity of a model increases naturally with the number or parameters which can again increase the computation time for fitting the model. While the average time for curve fitting is lower than 0.1 seconds for our uniform S-curves, it increases up to two to three seconds for the Bi-Richards curves. At the same time, length and development of the historical time series of a diffusion influence the performance notably, so that especially the comparatively complex Bi-S-curve models fail more often to provide practical probabilistic density intervals. The intervals of such models are so broad that the sharpness alone defines the WIS (Figure 2-2). In contrast, for models with a low impact of sharpness on the WIS, the values of the real diffusion lay more towards the upper or lower end of the probabilistic density intervals. Consequently, the risk for real values to even lay outside the intervals is comparatively high, e.g., with the uniform models of Bertalanffy and Richards.

Probabilistic projections for Switzerland

According to our forward-looking national probabilistic projections for Switzerland with training on historical data until 2021, the diffusion of solar PV, heat pumps, and BEV is unlikely to reach the levels that most scenarios from literature estimate as needed for a Swiss energy system with net-zero greenhouse gas emissions in 2050 (Figure 2-3a-c). The median of the projections of solar PV is at 12.5 GW in 2050, while most net-zero scenarios estimate total capacities that lay at the upper end of the probabilistic density interval, i.e., 25 GW (87% quantile) and higher. Only one study requires 14-15 GW (60% quantile) if Switzerland instead invests in wind power and natural gas, hydrogen or other thermal power plants (35). For the number of buildings with a heat pump, the median projects a number of around 570’000 buildings in 2050, while all net-zero scenarios estimate numbers that are more than twice as high and lay above the 90% quantile, i.e., 1.2 million. Similar holds true for BEV, where the projected median value of 1.4 million BEV is only half of the lowest net-zero scenario for 2050, i.e., 79% quantile. However, the projections of BEV for 2030 are in line with more scenarios from literature than the projections of solar PV and heat pumps and show a noticeably broader uncertainty range.

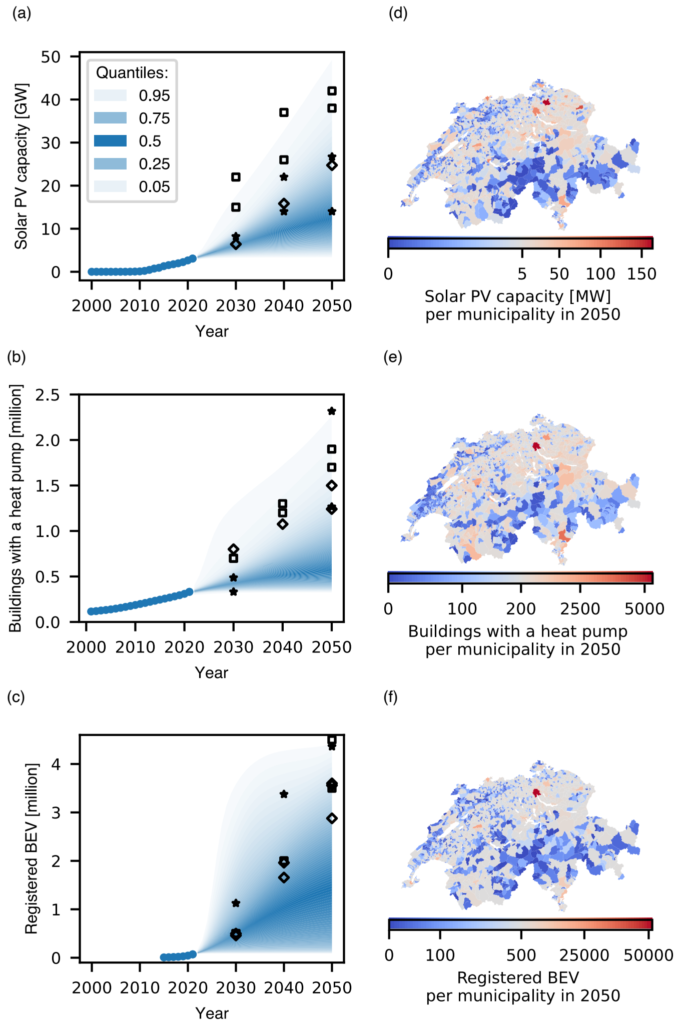

Figure 2-3. Probabilistic national projections (a-c) of the diffusion of solar PV, heat pumps, and Battery Electric Vehicles (BEV) in Switzerland until 2050 and maps (d-f) with the projected median values for each Swiss municipality in 2050, both with a quantile coloring scheme. The quantiles of the national projections are the sum of the corresponding quantiles of all municipalities. The black marker set targets for reaching an energy system of net-zero greenhouse gas emissions by 2050, estimated in studies for the Swiss Federal Office of Energy (◊) (34), (□) (38), and for the association of Swiss electricity companies VSE (*) (35). If different scenarios exist, highest and lowest values are shown.

Across Switzerland, it can vary notably by how much various municipalities have to increase their efforts to install and use solar PV, heat pumps, and BEV. The spatially-explicit projections for 2050 estimate that higher capacities are generally concentrated close to population centers, i.e., in the north-east of Switzerland and around larger cities (Figure 2-3d-f). Capacities are comparatively low in the south and in the north-west, which are both mountain regions of the Alps and Jura. This pattern is comparable to the diffusion in 2021 (Appendix 5.1.2.3). Regional differences are most extreme for BEV, where the number of BEV in the municipality with most BEV is 200 times higher than the median of all municipalities in 2050. For solar PV and heat pumps, the corresponding factors are 54 and 30, respectively. However, the projections for the diffusion per 100 inhabitants (Appendix 5.1.2.4) indicate that individual access to the capacities can still remain comparatively low in highly populated municipalities, e.g., around Zurich, Geneva, or Basel. Similar holds true for the shares of capacities over their technical potential (Appendix 5.1.2.4). Potentials remain largely unexploited: only when the Swiss municipalities follow the 99%

quantile path, 25% of municipalities might install more than 90% of their solar PV potential by 2050. For heat pumps, the corresponding shares are 36% of all municipalities and for BEV, 78%.

2.4 Discussion

With the examples of the three granular technologies of solar PV, heat pumps, and BEV, we show that our probabilistic projections provide both more accurate and reliable results than the respective deterministic projections and, at the same time, a more complete picture on the uncertainty. Not only is the MAPE of the probabilistic projections smaller, but also does the use of probabilistic density intervals and weighting of models compensate for problems that different projections of particular S-curve models can come with, e.g., underestimation, low saturation or exceptionally broad density intervals. While the extent can vary by which the probabilistic projections outperform the deterministic projections, it remains speculative which characteristics of the historical time series influence the performance of the projections to what extent. Our results plainly highlight that clear differences in the performance exist and that modelers should therefore avoid using single deterministic curves to project future diffusion of technologies.

With our investigated models and evaluation criteria, we find that combining different models into one weighted probabilistic projection reduces tradeoffs between advantages and disadvantages of single models. Especially the examples of Bertalanffy and some Bi-S-curves highlight that projections of a model might be accurate while their probabilistic density intervals are either too narrow, i.e., having a low sharpness penalty in the WIS, or too broad to be meaningful, i.e., having a high sharpness penalty. Assigning weights to the models can take such differences into account while at the same time it passes on uncertainties that are latent in the selection of models. The weighting must hereby be individual for each technology and its historical time series in a municipality. Although, the models of Bertalanffy and Richards most often receive highest weights, their weights can vary across the technologies, municipalities, and years in hindcasting. Therefore, modelers should always consider multiple models when creating projections of technology diffusion and test them by means of hindcasting.

However, the use of particular S-curve models and the determination of weights comes with high computational costs that can be out of proportion to the outcome. A model with more parameters might not eventually lead to more accurate projections. Examples of such are the four- and five-parameter Richards models that often create similar projections, while the five-parameter Richards needs more time to fit on the historical time series. The same is true for the Bi-Bertalanffy or other Bi-S-curve models that coincide with their respective uniform models that are faster to fit. The determination of weights takes time as hindcasting requires multiple repetitions of both curve fitting, and creating and evaluating probabilistic density intervals. Only if the fitted curves of different models are distinct, they might justify the computation of projections from different models. Since it can be difficult to predict whether the projections of different models are distinct for a particular technology or municipality, the use of multiple models might be inevitable nevertheless. Eventually, this uncertainty calls again for probabilistic density intervals in projections of technology diffusion.

The results and design of our approach have direct implications on how decision-makers on policies and infrastructure investments can use and interpret the probabilistic projections. First and foremost, the probabilistic approach provides information not only about the future trends of granular technology diffusion, but also about the likelihood of these trends. Two common methodological shortcomings are overcome this way: that projections induce overconfidence when they do not show uncertainties (39), and that, if shown, uncertainties are so broad that the projections become meaningless without information what is more or less likely (40, 41). Second, our projections reflect uncertainties in a way that depends on the quality and length of the historical time series of a diffusion and on parametrization and historical performance of the different investigated models. Even if we include Bi-S-curve models to account for the change in trends after, e.g., new policy, our approach for now provides only projections based on current diffusion dynamics. The approach hence cannot answer how future policies or context events, like subsidies or supply shortages, might accelerate or slow the projected diffusion. In line with

Kaack et al. (15) and Morgan and Keith (39), combining probabilistic projections with scenarios might help to further illustrate technology diffusion and its uncertainties. Third, as the quantile of a national projection is subject to the condition that all municipalities follow this quantile simultaneously, our national projections do not represent scenarios in which some municipalities perform higher or lower than the quantile. Mathematically, there are factorial of 214’800 scenarios (2’148 municipalities times 100 quantiles) possible, which are unpractical to calculate. Decision-makers may define specific scenarios of under- and overperforming municipalities before merging the projections of municipalities into a national projection.

In addition to decision-makers, the design of our methods has also direct implications on how modelers can use and interpret the probabilistic projections. Our methods rely on only few input assumptions, which make the methods applicable specifically to cases where the availability of different types of data is limited. However, our spatially-explicit projections rely on the availability of good-quality subnational data of high spatial resolution and for as long a historical time series as possible. Although our methods generally allow for lower spatial resolution than the municipality level, a lower resolution would provide less samples to create the probabilistic density intervals and would thus reduce the practicality of the intervals as they might become too broad or too poorly defined to be meaningful. The same holds true for short historical time series, as seen for BEV, where the density intervals are comparatively broad. Consequently, modelers might have to adjust the way we create the intervals and use additional input parameters. Drawing projections only from historical time series of a diffusion is justified as the time series implicitly include technological, socio-economic and political factors that drive the diffusion (23). Nevertheless, if additional data is available, the use of such factors might improve the projections (33). At the same time, the use of alternative diffusion models, evaluation criteria or types of weighting can influence the projections. Although we provide an analysis of multiple models and criteria, future work can investigate them further and analyze how the use of different criteria impacts the choice of models in different years of a technology diffusion.

2.5 Materials and Methods

Data. The data used in our study are publicly available at different spatial resolutions and for different time periods (42–44). For consistency, we aggregate all data to the 2’148 Swiss municipalities that existed at the end of 2021 (45, 46) and start the time series of technology diffusion in the first year of available data. The dataset of solar PV registers all installations from 2000 – 2021 that are in use and have a minimum capacity of 2 kW (42), covering 89% of the real existing total capacity (47). We use solar PV capacities that are attached to or integrated in buildings and make up around 96% of the available dataset of solar PV in Switzerland (42). We approximate the number of heat pumps in 2001 – 2021 with the number of buildings that are registered in the Swiss Federal Register of Buildings and Dwellings (43) and heated by at least one heat pump as a primary or secondary heating system for space heating or warm water. See Appendix 5.1.1.3 for a detailed derivation of the time series. The dataset of BEV records the numbers of all civil passenger cars registered at the post address of their owners in 2015 – 2021 (44). For analyzing diffusion per number of inhabitants, the population sizes per municipality are available for the years 2000 and 2007 – 2020 (48) and we linearly interpolate them for 2001 – 2006 and use the numbers of 2020 also for 2021. For analyzing diffusion per unit of maximum technical potential, we use the technical potential of solar PV on currently existing roofs and facades (49) in kW with local capacity factors (50, 51), see Appendix 5.1.1.4. For heat pumps and BEV we use the currently existing number of buildings (43) and civil passenger cars (44), respectively.

Methods. Our four-step process to create a probabilistic projection consists of two main parts: the creation of deterministic projections and probabilistic projections for each S-curve model (steps 1 and 2 in Figure 2-1), and the creation of a final projection that combines the probabilistic projections of the models (steps 3 and 4 in Figure 2-1). Appendix 5.1.1.1 shows each step and the underlying assumptions in detail. Prior to the four steps, we remove municipalities with missing, quasi-static or highly fluctuating historical time series from our dataset and use mean growth rates and model weights of all municipalities for the projections (Appendix 5.1.1.5). We exclude municipalities with historical time series in which one of the last three values is zero, the last five (for BEV: three) values are the same, or the values drop by half or more from one year to another. Correspondingly, we remove for solar PV, heat pumps, and BEV 2.5%, 3.5%, and 16.6% of municipalities, respectively.

In the first part, we fit twelve different S-curve models on the historical time series of the diffusion of a technology to create twelve deterministic projections. The curve fitting uses differential evolution and non-linear least squares optimization to minimize the residuals of a curve to the given points of the time series to find the optimal set of parameters of a curve. For details, see Appendix 5.1.1.6. Then, we create one probabilistic projection for each S-curve model by combining all deterministic projections of similar municipalities for each model and calculating the quantiles of the resulting distribution. Before combining, we normalize the deterministic projections using the value of the last year used for curve fitting and afterwards multiply the quantiles with the last value of the historical time series of the considered municipality. We consider two municipalities similar if the mean Euclidean distance between their normalized historical time series is lower than the 30% quantile of the mean Euclidean distances to all municipalities. See Appendix 5.1.1.2 for sensitivity analysis and discussion of the chosen 30% quantile.

In the second part, we evaluate the performance of each probabilistic projection using iterative hindcasting. For this, we repeat steps 1 and 2, vary the years used for curve fitting and evaluation in each iteration, and calculate metrics of model performance relative to each observation for one- to ten-year-ahead projections of solar PV and heat pumps, and one- to four-year-ahead projections of BEV. The metrics include:

- The share of curves saturating below the time series value of 2021;
- MAPE to take the different scales of technology diffusion across the municipalities into account;
- WIS as the sum of sharpness and calibration, and with the use of interval weights that approximate the WIS to the percentage version of the continuous ranked probability score (37, 52).

Based on the performance of the twelve S-curve models, we assign weights that are individual for each municipality and use the weights to combine the probabilistic projections. We derive the calculation of weights from methods of ensemble weather forecasting where the use of inverse error variance outperforms equal weighting (53, 54). The mean squared WIS acts as the error variance in our case.

S-curves. The S-curve models we investigate are listed below and comprise six uniform models and linear combinations of each uniform model with itself, creating six Bi-S-curves to model two growth phases, e.g., due to change in policies. We investigate two common symmetric S-curves, i.e., logistic and Bass, and four asymmetric curves, i.e., Gompertz, Bertalanffy, a four-parameter and a five-parameter version of the generalized Richards model (all asymmetric). The function value *f(t)* describes the installed capacity or number of solar PV, heat pumps, or BEV in their specific units, e.g., kW, in year *t*. We add a vertical shift *z* so that the curves can handle time series that begin with non-zero values. *(C-z)* is the level of saturation and both *C* and *z* have the same unit as *f(t)*. The time shift t_0 is given in years, while *p, q, k, d* and *b* are unitless curve parameters that are specific to each curve. See Appendix 5.1.1.6 for parameter limits.

Bass (adapted from (55)):

$$f(t) = (C - z) \cdot \frac{1 - \exp\big(-(p+q)(t-t_0)\big)}{1 + \frac{q}{p} \cdot \exp\big(-(p+q)(t-t_0)\big)} + z \qquad (1)$$

Bertalanffy (adapted from (23)):

$$f(t) = (C - z) \cdot \big(1 - b \cdot \exp\big(-\mathrm{k} \cdot (\mathrm{t} - t_0)\big)\big)^3 + z \qquad (2)$$

Gompertz (adapted from (30, 56)):

$$f(t) = (C - z) \cdot \exp\big(-\exp\big(-k \cdot (t - t_0)\big)\big) + z \tag{3}$$

Logistic (adapted from (29)):

$$f(t) = \frac{C - z}{1 + \exp\,(-k \cdot (t - t_0))} + z \tag{4}$$

Richards-4p (adapted from (30)):

$$f(t) = (C - z) \cdot \left(1 - \frac{1}{d} \cdot \exp\big(-\mathrm{k} \cdot (\mathrm{t} - t_0)\big)\right)^{d} + z \tag{5}$$

Richards-5p (adapted from (23)):

$$f(t) = (C - z) \cdot \big(1 - b \cdot \exp\big(-\mathrm{k} \cdot (\mathrm{t} - t_0)\big)\big)^{d} + z \tag{6}$$

Comparison with net-zero scenarios. To compare the probabilistic projections of the diffusion of solar PV, heat pumps, and BEV in Switzerland, we add a set of target values from studies that model a Swiss energy system reaching net-zero greenhouse gas emissions by 2050. If a study provides different scenarios, we add the highest and lowest values. Two studies for the Swiss Federal Office of Energy (34, 38) provide targets that complement the measures of the Swiss government to decarbonize the Swiss energy system (57). The scenarios of the studies model different shares of electrification, heating networks and biofuels and their implications on the power grid. The association of Swiss electricity companies VSE reports scenarios that analyze the level of integration of Switzerland in the European energy market and different rates of infrastructure investments (35). For solar PV, we convert annual generation levels into capacities using the national average of local capacity factors at 0.155 (50, 51). For heat pumps, we convert the increase in heat supply using the heat supply of the reference years of the studies and the number of buildings in the Swiss Federal Register of Buildings and Dwellings (43). For BEV, we multiply shares with the total number of civil passenger cars in 2021 (44).

Data availability. The probabilistic projections of solar PV, heat pumps and BEV for all 2'148 Swiss municipalities are provided at Zenodo, including annual updates using the latest available data: https://doi.org/10.5281/zenodo.8414845**.** The historic time series data is publicly available at Swiss Federal Office of Energy (42) and Federal Statistical Office (43, 44).

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3 Comparison of statistical and optimization models for projecting future PV installations at a sub-national scale

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3.1 Abstract

Spatially-disaggregated projections of new solar photovoltaic (PV) installations are essential for planning electricity grids and managing the electricity system at large scale. Such projections at sub-national level can be obtained by statistical or by electricity system optimization models, but there is barely any study that compares the performances of the two approaches. This study aims to project and compare PV installations at a level of 143 districts in Switzerland, using a simple extrapolation method (as a benchmark of the common practice today), a multiple linear regression model, two spatial regression models, and a spatially-explicit optimization model (EXPANSE) with various features to account for policy. The performance of different approaches is evaluated retrospectively for 2012 – 2020, using multiple accuracy indicators. The evaluation results show that statistical regression models, which account for socio-demographic and techno-economic characteristics as predictors of future PV growth, overall perform better than simple extrapolation or optimization. Although commonly used, extrapolation has the highest variability in accuracy, indicating the least robust performance. The optimization model tends to underestimate PV installations in its least-cost scenarios, if the role of policy is not considered. Incorporating solar PV policies and renewable electricity generation targets increases the overall accuracy of the optimization model at a national level, but not necessarily at a spatially-explicit level. We thus conclude that statistical models are preferred for projecting future PV installations at a sub-national scale.

3.2 Introduction

The transformation of the electricity sector is essential in pursuit of today's emissions reduction targets, especially with the need to electrify and decarbonize the entire energy system [1]. Renewable electricity technologies are a key pillar of this transformation, but planning reliable electricity systems based on such technologies is challenging due to weather dependency and uncertainty in future diffusion [2,3]. One key challenge is to project future installations and not only the operation of variable renewable electricity sources, such as solar PV, to inform planning of the electricity grids and management and policy of the whole system transformation [4]. Optimization-based energy system models provide crucial policy support by shedding light on technically plausible and least-cost transformation scenarios, mostly at a highly spatially aggregated national level [3,5]. Planning of the energy system with high shares of renewable technologies, however, requires improving the spatial resolutions of the models [6–9]. Electricity generation from weather-dependent solar PV installations are greatly depending on the spatial location and this influences the need for supporting infrastructures like grids or storage [10–12] as well as solar PV costs under different energy scenarios [13].

Various methods are currently used to spatially project future installations of renewable electricity technologies. The simplest and most intuitive method is the extrapolation based on the historical data, which assumes that PV installations will grow spatially in the future similarly compared to the past [14,15]. In the cases where spatial historical data is available, statistical models are used to explain the drivers of technology uptake [16–19] and sometimes also to make projections [20,21]. For example, socio-demographic, geographic and economic characteristics were predictors of spatial solar PV adoption in Germany [22,23], in England and Wales [24], the Netherlands [25], and Switzerland [19], while geographic and technological characteristics were predictors of utility-scale PV facilities worldwide [26]. In the case of Switzerland, Müller and Trutnevyte [21] further investigated how the key predictor variables from statistical models could be used to project future PV installations and assessed the performance of the statistical models using out-of-sample testing with historical data. Besides extrapolation and statistical regression methods, optimization-based energy or electricity system models are also often used to obtain spatial projections at sub-national level, including HighRES [11] or ESME [13] for UK, JRC-EU-TIMES [27] for Austria, EXPANSE for Switzerland [15] or Europe [28,29], Calliope for Europe [30], and others. However, broader critiques of optimization-based models argue that optimization does not sufficiently reproduce the real-world trends at a national [31,32] or sub-national level [15]. In sum, there are barely any studies on the evaluation and comparison of the different modeling methods regarding their performances in spatially projecting renewable energy installations.

In terms of accuracy evaluation of energy system models, some studies use historical data and retrospective modeling with [21,33] or without out-of-sample testing [31,32] to conclude which models are more accurate. In the case of out-of-sample testing, historical data that is used for testing the projection's performance is not included in the model fitting and training [21,33,34]. Most studies assess the accuracy with only one model performance indicator. For example, Marcy et al. [35] evaluated temporal disaggregation methods in the capacity expansion model with different spatial resolutions by quantifying root-mean-square error (RMSE). al Irsyad et al. [36] evaluated capacity and generation projections of variable renewable electricity sources by quantifying mean percentage error (MPE) and mean absolute percentage error (MAPE). Müller and Trutnevyte [21] evaluated accuracy of spatial models of solar PV by applying root-mean-squared logarithmic error (RMSLE). Kaack et al. [33] used mean absolute percentage error (MAPE) and mean absolute logarithmic error (MALE) to assess projections of 18 energy-related quantities in national-level US projections. More recently, Wen et al. [37] summarized various accuracy indicators used in literature and identified a suite of five most informative indicators. The study shows that more than one indicator is needed to obtain reliable evaluation outcomes in multiple dimensions, but such a comprehensive accuracy evaluation is still rare.

This study aims to compare projections of PV installations from different statistical models and the optimization model during 2012–2020, by using a spatial dataset of 114'089 PV installations in 143 districts of Switzerland. Using out-of-sample evaluation, we compare the accuracy of projections obtained by simple extrapolation (as a benchmark of the common practice today), spatially-disaggregated statistical regression models with and without spatial effects, and the spatially-explicit cost optimization model EXPANSE with various features to account for the role of policy. We aim to answer these research questions: (i) how accurate are the projections of new PV installations, generated by extrapolation, statistical and optimization models, and (ii) what can we learn from this comparison for modeling forward-looking spatial projections of new renewable technologies.

3.3 Methods

Three modeling approaches are used to generate spatially-disaggregated projections of new PV installations at level of 143 districts in Switzerland: a simple extrapolation method that is commonly used today, regression models with or without spatial effects, and least-cost based EXPANSE electricity system optimization model. First, historical spatial PV installation data in Switzerland in 2010–2020 is collected (Section 3.3.1). Then, we use the extrapolation method (Section 3.3.2.1) and three statistical regression models, including multiple linear regression model (MLR), spatial simultaneous autoregressive lag model (SAR) and spatial simultaneous autoregressive error model (SEM), to project the cumulative PV capacity in each district by 2020 (Section 3.3.2.2). Regression models use socio-demographic and techno-economic characteristics as dependent variables (predictors), and their out-of-sample accuracy is evaluated. Finally, the spatially-explicit EXPANSE electricity system model is also applied as a cost optimization model to obtain the PV capacity projections at the district level (Section 3.3.2.3) under various implementations of policy assumptions. Finally, three approaches are evaluated and compared using several accuracy indicators (Section 3.3.3).

3.3.1 PV data

In this study, publicly available data [38] of PV installations in Switzerland is used, including information on the installed capacity, start date of operation, and location. The dataset recorded 114’089 of PV projects and about 2.7 GW of PV capacity in Switzerland by the end of 2020. For the analysis, we choose the time frame of 2012–2020, when there were sufficient PV units in Switzerland for the spatial statistical models to be used (Section 3.3.2.2). The PV installation data is pre-processed by spatially aggregating the data at a level of 143 districts. District level is found to be an appropriate spatial resolution in equivalent spatial analyses studies considering the average surface area and the population of the district in other similar studies [21]. To compare the projections of different models, we consider the annual cumulative PV capacity in each district as our dependent variable in statistical models, which can be easily compared with the extrapolation and optimization result.

3.3.2 Three modeling approaches

3.3.2.1 Extrapolation

As a benchmark, we first apply extrapolation to project PV installations at a district level because extrapolation is commonly used for spatial projections due to its simplicity. The commonly used extrapolation method is based on linear fitting of available historical data [39–41]. Armstrong [42] summarized the conditions under which the extrapolation is preferred, such as the short-term forecasting method, stable trend assumption, and limited historical information. These conditions could be considered acceptable in our case. We apply the simplest linear extrapolation: the PV installed capacity projection in year y is based on the PV installed capacity in 2010 and in year y-1, assuming a stable trend of the yearly average increase of capacity by the end of year y-1.

3.3.2.2 Statistical regression models

The strength of statistical models is that they do not only use information on historical PV growth, like in the case of extrapolation, but also consider various socio-demographic and techno-economic characteristics as predictors of future PV growth. Three statistical regression models are used here from the previous study [21], including a multiple linear regression (MLR) model and two spatial regression models, i.e. a spatial simultaneous autoregressive lag model (SAR) and a spatial simultaneous autoregressive error model (SEM). For the two spatial models, we use two methods to define the spatial weight matrix: rook contiguity weights (Rook) and radial distance-based weights (Dist), leading to four spatial regression model types: SAR.Rook, SAR.Dist, SEM.Rook and SEM.Dist.

Two categories of predictor variables are used to obtain the spatial PV diffusion in the regression models: techno-economic variables and socio-demographic variables (Table 3-1). A comprehensive literature review has been carried out in a previous study [21] to identify and statistically test the most relevant predictor variables. For the current study, we additionally updated the techno-economic and socio-demographic data until 2020. Based on the study by Nuñez-Jimenez et al. [4], we then used the net present value of PV as a new economic profitability variable, instead of using the electricity price and return on investment separately as in [21]. The use of net present value enables us to include spatial data of support mechanisms for solar PV (subsidies and feed-in tariffs for different sizes of PV installations) and avoided costs due to self-consumption of electricity for different years. Other variables kept the same definition as in [21]. The exploitable solar PV potential is obtained from the Opendata.swiss of Swiss Federal Office of Energy [43] as a predictor that assessed the PV potential based on roofs and facades. The age coefficient is defined as the percentage of people greater than 65 per 100 people with $20 \leq$ age ≤ 65. Due to skewed distributions, different units and order of magnitudes, all predictor variables were log-transformed and standardized by subtracting the mean from each value and dividing it by the standard deviation. The spatial data that is used to determine the spatial weights in regressions is kept the same as in the previous study by Müller and Trutnevyte [21], since there are no changes regarding the geographical boundaries of Swiss districts.

Table 3-1. Response and predictor variables used in the statistical regression models for each district.

Dependent variables	**Explanation**	
PV capacity	Cumulative installed PV capacity (kW)	
Techno-economic predictors	**Unit**	**Year**
Exploitable solar PV potential	GWh/year	2018 (issued)
Electricity demand per capita	kWh/capita	2010–2020
Net present value (profitability)	CHF/kWh	2010–2020
Socio-demographic predictors	**Unit**	**Year**
Population density	Capita/km^2	2010–2020
Household size	Number of persons	2014–2019
Age coefficient	%	2011–2020
Green voters	%	2011, 2015, 2019
Net income	CHF/capita	2010–2020

Note: All data was collected annually at the district level. The household size data is given until 2019 so 2019 data is used for 2020.

In this study we use one-year-ahead out-of-sample projections. A previous study [21] found that the accuracy of out-of-sample projections is lower than the accuracy of in-sample projection and can be improved by including the time-lagged response variable as a predictor variable. Hence in this study we include the PV installed capacity of *y-1* as a predictor variable when obtaining the out-of-sample spatial PV capacity projection of *y*.

3.3.2.3 EXPANSE optimization model

The single-year electricity system model EXPANSE with a spatial resolution of 2'169 municipalities is used to generate the least-cost configurations of the whole electricity supply system in Switzerland, including the spatial distribution of PV installations. EXPANSE (EXploration of PAtterns in Near-optimal energy ScEnarios) is a bottom-up, perfect-foresight and technology-rich electricity system model [15,28,29]. The model minimizes the total annual electricity system costs, including annualized investment, operation, maintenance, and fuel costs of electricity generation, storage, and transmission infrastructure. More details on model description and the mathematical formulation can be found in [15,28,29]. The EXPANSE model is run for each year in 2012–2020 individually, with an hourly time resolution. Most historical data on technologies and costs is acquired from the original EXPANSE dataset [15,28,29] and the study of Jaxa-Rozen et al. [44]. Hourly load profiles from 2012 to 2020 are collected from Swissgrid [45]. For rooftop solar PV, the costs are assumed to be equal to the values in the regression models (Section 3.3.2.2). The import/export prices for electricity are adapted from UN Comtrade database [46]. After running EXPANSE, we aggregate the PV installation capacity from municipality to district level to be consistent with the statistical regression models.

In 2012–2020, Switzerland had various policies to promote PV deployment at federal and subnational levels [47] and it was in the process of implementing the Energy Strategy 2050 that defines renewable energy targets [48]. Four distinct scenarios are hence generated with EXPANSE by modifying the model's features to account for the role of policy: the reference scenario or EXPANSE.Basic scenario (least-cost scenario without policy), the PV policy scenario (EXPANSE.PV), the scenario with target on renewable energy sources (EXPANSE.RES), and the combination of both (PV policy with RES target, called EXPANSE.PV and RES). The PV policy scenario EXPANSE.PV considers policies that aimed to boost solar PV deployments and reduce the PV costs, such as subsidies and feed-in-tariff revenues; these are the same policies that were included in the profitability calculations in the statistical models (Section 3.3.2.2). The RES target scenario includes a 2035 target of 17 TWh of electricity from solar PV, wind power and biomass in Switzerland by 2035 based on the Swiss Energy Act [49]. On that basis, we set annual renewable electricity generation targets in 2012–2020 by interpolation with a starting point in year 2011. In the scenario with PV policy and RES target, both PV policy and RES target are considered to obtain the least-cost scenario generated by EXPANSE.

3.3.3 Accuracy analysis

To evaluate the retrospective performance of extrapolation, three regression models, and EXPANSE optimization model in 2012–2020 as compared to the real-world spatial PV deployment (Section 3.3.1), we apply several complementary accuracy indicators. Wen et al. [37] summarized the indicators that are used for accuracy assessments of energy system models and identified a small suite of indicators that are the most informative. Following this work, we choose two indicators to be used together: symmetric mean percentage error (sMPE) and symmetric mean absolute percentage error (sMAPE). sMPE indicates direction of the error, that is, whether the output is overall over-projected or under-projected. Since it calculates the mean percentage (relative) error with signs, sMPE is affected by offsetting between positive and negative errors. Therefore, sMAPE is needed as a complementary accuracy indicator because it indicates the absolute percentage error and hence shows the full magnitude of the error. More discussion on the two indicators and their formulas can be found in [37].

3.4 Results

3.4.1 Results of statistical models

We first look at the performance of three statistical models: MLR, SAR and SEM, with two spatial weighting methods applied to the spatial models of SAR and SEM, respectively (Rook and Dist). Based on Table 3-2 with results in terms of the cumulative installed PV capacity in 2020, R2 values show that at least 90.4% to 92% of variance in PV capacity can be explained by the predictor variables shown in Table 3-1. We calculate the adjusted R2 in MLR and Nagelkerke pseudo R2 in spatial models. Also, we assess the models by the Akaike information criterion (AIC) that evaluates both the fitting and the model simplicity to avoid overfitting. The highest R2 and the lowest AIC suggest that the SEM.Rook model has the best performance, followed by SEM.Dist, SAR.Dist, SAR.Rook, and MLR. The parameter ρ in SAR models and λ in SEM models are coefficients of spatial components, thus their values and significance show whether the inclusion of the spatial components improves the model. The high λ values and their high significance show that there are high spatial autocorrelations in residuals, hence the regression results can be largely improved by spatial SEM models. ρ values in SAR models are lower and less significant, showing that the inclusion of spatial autocorrelation in dependent variable is less important regarding regression improvement.

Table 3-2. Results of the statistical models in predictive installed PV capacity per district in Switzerland in 2020. The five spatial regression methods are multiple linear regression (MLR), spatial simultaneous autoregressive lag model with rook contiguity weights (SAR.Rook) and with radial distance weights (SAR.Dist), spatial simultaneous autoregressive error model with rook contiguity weights (SEM.Rook) and with radial distance weights (SEM.Dist).

Predictors	MLR	SAR.Rook	SAR.Dist	SEM.Rook	SEM.Dist
Expl. PV potential	0.726*** (0.029)	0.713*** (0.029)	0.716*** (0.028)	0.749*** (0.028)	0.732*** (0.028)
Net present value	0.076** (0.028)	0.085** (0.027)	0.080** (0.027)	0.061* (0.026)	0.066** (0.026)
Electricity demand	0.057* (0.028)	0.048* (0.027)	0.052 (0.026)	0.033 (0.025)	0.035 (0.026)
Population density	0.249*** (0.039)	0.220*** (0.039)	0.208*** (0.040)	0.215*** (0.042)	0.210*** (0.041)
Household size	0.252*** (0.032)	0.238*** (0.031)	0.225*** (0.032)	0.226*** (0.029)	0.238*** (0.030)
Age coefficient	0.014 (0.038)	0.028 (0.036)	0.024 (0.036)	0.007 (0.036)	0.010 (0.037)
Green voters	-0.015 (0.027)	-0.017 (0.026)	-0.011 (0.025)	-0.003 (0.027)	0.007 (0.027)
Net income	-0.093** (0.031)	-0.094** (0.029)	-0.092** (0.029)	-0.065* (0.030)	-0.063* (0.030)
Constant	9.490 (0.024)	8.361 (0.487)	7.814 (0.651)	9.489 (0.043)	9.494 (0.049)
ρ		0.118*	0.176*		
λ				0.493***	0.546***
R^2	0.909	0.913	0.913	0.920	0.916
Adjusted R^2	0.904				
AIC	65.243	61.773	60.689	49.287	56.355

$* \ p \leq 0.05$; $** \ p \leq 0.01$; $*** \ p \leq 0.001$.

In terms of the predictor variables, their regression coefficients are comparable in all the models with rather minor differences. The exploitable solar PV potential, household size and population density are the three variables that have the most significant positive effect on PV installed capacity. Compared to MLR, the exploitable solar PV potential shows higher effect in SEM models and lower effect in SAR models. Household size and population density have higher effect levels in MLR than in spatial models. Net income (with negative effect) and net present value (with positive effect) are also statistically significant predictors in all spatial models, but they have lower significance for SEM models. Electricity demand is statistically significant for MLR and SAR.Rook, but not for other models. Age coefficient and green voters are not statistically significant predictors compared to other variables. This is consistent with the results in previous literature [21], where these two predictors are found not to be statistically significant for PV installed capacity, while they are significant for other dependent variables, such as the number of PV projects and projects per capita.

3.4.2 Overall comparison of individual models

To evaluate the projection accuracy of extrapolation, statistical models, and the EXPANSE optimization model, we compare the total cumulative installed PV capacity in Switzerland in 2012–2020 in the real world and for the 1-year-ahead out-of-sample spatial projections (Figure 3-1). To evaluate the projection accuracy of the models, we compare 1-year-ahead spatial projections of the total cumulative installed PV capacity in Switzerland with the real-world development (Figure 3-1). The installed PV capacity increased from around 500 MW in 2012 to around 2’700 MW in 2020 (see real-world data). Most of the time, all the models underestimate this increase in capacity, except for the over-projections in the statistical models in 2014, 2016 and 2018, and in the extrapolation in 2014, 2017, and 2018. All the statistical regression models show similar PV capacity projection outcomes since 2014. SAR models, especially SAR.Dist, show higher projection accuracy in early years of 2012 and 2013. Compared to regression models, the extrapolation overall shows similar or higher deviations from the real world, except for the year 2014 and 2016. The installed PV capacity projections from EXPANSE model are underestimated under basic scenario, because solar PV installations are not the most cost-efficient investments as compared to the other electricity generation technologies in the optimization model. We find that solar PV cost reduction due to PV-specific polices (EXPANSE.PV in Figure 3-1) promoted the PV deployment in EXPANSE to various extents over the years, but still underestimated the overall installed capacity as compared to statistical and even extrapolation models. When renewable electricity target is added to EXPANSE without PV policy (EXPANSE.RES), the model still continues to underestimate PV because it chooses other technologies, like wind power, to meet the target. Only when renewable electricity targets and PV policies are combined (EXPANSE.PV and RES), the installed PV capacity is increased more substantially, but then leading to an overall over-projection in years 2012, 2014, 2016 and afterwards.

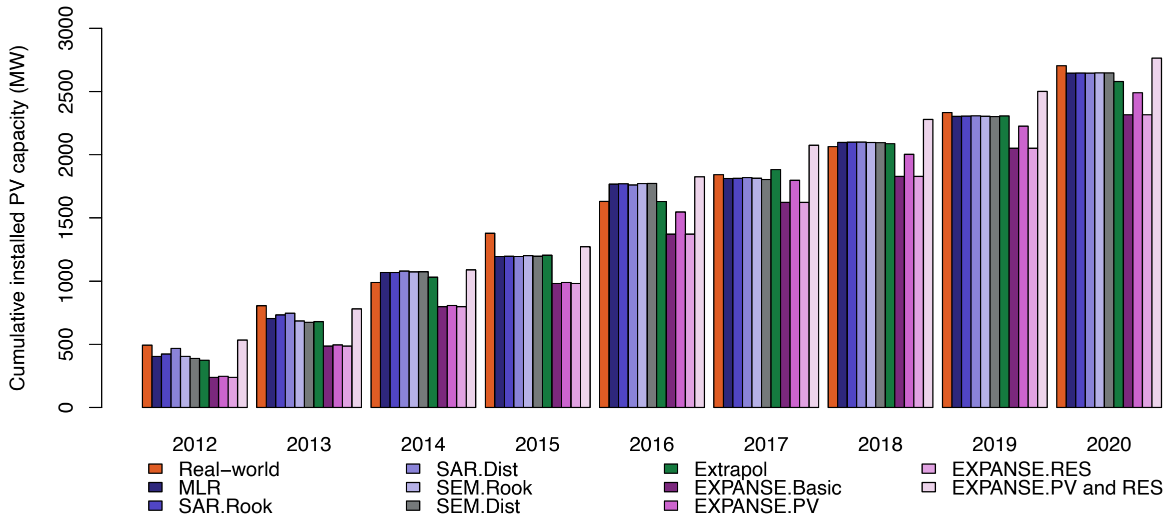

Figure 3-1. Cumulative installed PV capacity of real-world data and by 1-year-ahead projections with statistical regression, extrapolation, and EXPANSE optimization models in Switzerland in 2012–2020. The three statistical models are MLR (multiple linear regression model), SAR (spatial simultaneous autoregressive lag model) and SEM (spatial simultaneous autoregressive error model). The two methods to define the spatial weight matrix are Rook (rook contiguity weights) and Dist (radial distance-based weights). The four scenarios modeled in EXPANSE are Basic (the reference scenario without PV policy and the

renewable generation target), PV (scenario with PV policies), RES (scenario with renewable generation target), and PV and RES (scenario with both PV and RES).

If we observe spatial-disaggregated relative deviations for each district in, for example, 2013 and 2020 (Figure 3-2), the projection accuracy has remarkably increased in 2020 compared to 2013 for all models, and regression models perform best compared to extrapolation and the EXPANSE model. Similar to the total installed capacity shown in Figure 3-1, the district-level projections of installed PV capacity by different regression models show more differences in 2013 than in 2020. The spatial regression models overall show spatially similar deviations and, because of limited data availability for early years, their performance in 2013 is not yet as good as in 2020. There are evident under-projections (in dark blue in Figure 3-2) in central and west Switzerland in 2013, especially for MLR and SEM models, as well as over-projections (in pink) in the southern districts in 2013. These deviations in spatial models become marginal by 2020. The extrapolation method has the tendency to underestimate the projections at a spatially-disaggregated district level, especially in 2013, when there were rapid emerging PV deployments. The most evident deviations are observed in the region of Maloja in the Southeast, due to a more than doubled installed capacity in the region (1.39 MW in 2013 and 3.39 MW in 2020). Similarly, this sudden increase was not captured by the extrapolation method. The EXPANSE optimization model (EXPANSE.Basic) shows the highest tendency to under-project the PV installations in 2013 not only overall (Figure 3-1), but also by district (Figure 3-2), but this performance improves towards 2020. In contrast, in scenarios with PV policy (“EXPANSE.PV” and “EXPANSE.PV and RES”), the districts in southeast (such as Maloja) have the tendency of over-projection because of the lower investment costs with solar PV subsidies and feed-in-tariff revenues.

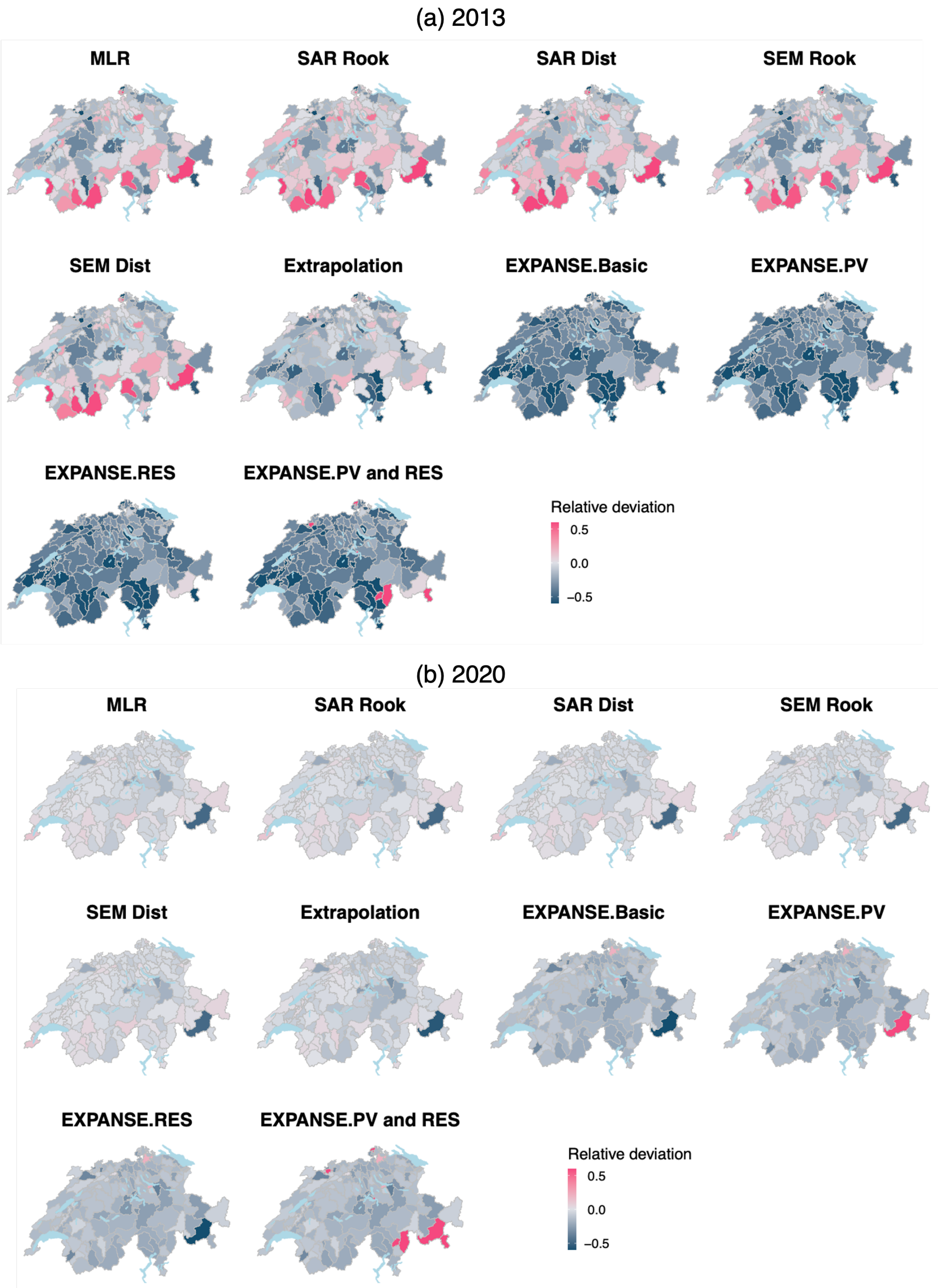

Figure 3-2. Spatial-disaggregated relative deviations of installed PV capacity at a district level in Switzerland in 2013 and 2020 for the presented models. MLR (multiple linear regression model), SAR (spatial simultaneous autoregressive lag model) and SEM (spatial simultaneous autoregressive error model). Two methods to define the spatial weight matrix are Rook (rook contiguity weights) and Dist (radial distance-based weights). Four scenarios modeled in EXPANSE are Basic (the reference scenario without PV policy and the renewable generation target), PV (scenario with PV policies), RES (scenario with renewable generation target), and PV and RES (scenario with both PV and RES). Relative deviation is defined as $(y_{projection} - y_{real})/y_{real}$.

3.4.3 Detailed accuracy analysis

For a more detailed analysis, we use two accuracy indicators sMAPE and sMPE to calculate the spatially-aggregated errors per district for each year, and assess the performance of the regression models, extrapolation, and the EXPANSE optimization model regarding their year-ahead PV installed capacity projection (Figure 3-3). sMPE quantification results show that the PV installed capacity is overall under-projected in the period 2012–2020, except for 2014, 2016 and 2018 with regression models and 2014, 2017 and 2018 with extrapolation. The maximum sMPE value of 9% (over-projection) occurred in 2014 for SAR.Dist model. The minimum sMPE values are observed in 2012 for all the models, indicating the occurrence of largest under-projections in this year. In early years of 2012 and 2013, SAR models have the highest accuracy with up to 14% lower sMPE than other regression models, 31% lower than the extrapolation, and 69% lower than the EXPANSE model. In later years, especially since 2015, sMPE values of regressions models become similar, with a difference of less than 1% since 2015. The sMPE of the extrapolation method shows a higher yearly variability compared to regression models and EXPANSE model scenarios. The high variability points towards a large cancelation effect between positive and negative errors and, a vulnerable and less robust performance than in the case of statistical and optimization models.

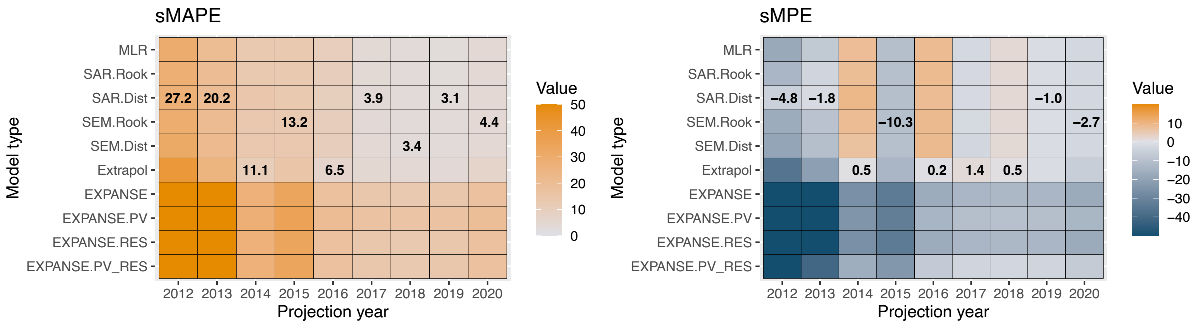

Figure 3-3. Accuracy indicators of symmetric mean percentage error (sMPE) and symmetric mean absolute percentage error (sMAPE) for assessing the total PV installed capacity projections in 2012–2020 in Switzerland on the basis of spatial results per district. The best performances (the minimum values) for each year are annotated with values.

Instead of showing the direction of the overall projections, sMAPE quantifies the mean absolute magnitudes of errors. The yearly minimum sMAPE values occur most often with the SAR.Dist model in 2012 and 2013, with extrapolation in 2014–2016 and with both SAR and SEM models since 2017. Since 2014, sMAPE values of regressions models become similar, with a marginal difference of less than 1%. From sMPE quantification, extrapolation seems to have better performance in 2016–2018, while sMAPE values indicate that since 2017, the spatial regression models perform better. This is because there are large offsets between positive and negative errors in extrapolation method. The large offsets with the extrapolation, e.g. low sMPE (less or equal to 0.5%) and high sMAPE in 2014, 2016 and 2018, indicate that the PV capacities are over-projected in about half of the districts, while under-projected in others. Overall, the extrapolation shows an evenly distributed deviations, and less spatially-relevant projection results. The EXPANSE scenarios show the highest annual sMAPE, while the accuracy is showing a tendency of improving, with the sMAPE values within 17% since 2016, and the lowest value of 13.4% in 2018 in three scenarios (Basic, RES, and PV with RES). While the lowest sMAPE value of 13.4% occurs in 2018 for EXPANSE model, the lowest values occurred in 2019 (3.1%) for all the regression models and the extrapolation method. The largest sMAPE values for all models are in 2012. Plausible reasons for the large errors in early years are the small dataset and rapid PV installation increases in 2011–2013 with up to 100% increase per year. The unexpected sudden annual changes are not captured by the regression models that are fitted with only the 2011 dataset, leading to a low model fit accuracy.

In the EXPANSE optimization model, the PV investment costs are relatively high compared to other electricity generation technologies in early 2010s, hence PV installation is not preferred in the model, while the real world witnessed a rapid PV capacity expansion during this period. Among all EXPANSE scenarios, the highest accuracy is reached in the scenario PV with RES (EXPANSE.PV and RES), where both the lowest sMAPE and sMPE are observed, and sMPE values are much lower than sMAPE. By comparing the two indicators we again find the evidence that the lower sMPE values do not necessarily indicate the lower deviation due to the offsets between over-projections and under-projections among districts. Indeed, there are over-projections in several southeastern districts (Figure 3-2) in the scenario PV with RES, leading to a lower overall sMPE compared to other scenarios.

3.5 Discussion

In this study we compared extrapolation, statistical and optimization models for projecting future spatial PV installations at a district level in Switzerland in the short run. Overall, the statistical regression models that rely on socio-demographic and techno-economic characteristics as predictors of future PV growth have the best accuracy performance, followed by extrapolation and then the EXPANSE optimization model with or without policy feature. The presented five statistical regression approaches, including MLR, SAR.Rook, SAR.Dist, SEM.Rook and SEM.Dist, have relatively high accuracy in projecting PV capacity in out-of-sample evaluations, with relatively small differences among the models for the projections since 2015. This is consistent with the previous study of Müller and Trutnevyte [21], where the out-of-sample evaluations of PV capacity projections were equally good for different regression models. The regression parameters shown in Table 3-2 indicate that without the time-lagged response variable as the predictor, the fitting performance of SEM models is the best, since the regression model performance improved the most under SEM with the inclusion of spatial dependence in the residuals. For regression models, yearly deviations mostly occur in 2012, 2013 and 2015, mainly due to the drastic yearly increases in PV deployment in the real world and less reliable year-ahead fittings in these years. The sMPE and sMAPE values of the regression models have the least yearly variability compared to the optimization model and the extrapolation. This indicates that the statistical regression models have more robust performances for short-term spatial projections of new PV capacity. The robustness comes from the well-chosen independent variables (socio-demographic and techno-economic predictors), from a history-informed logic of how PV is adopted, and from the better model fits considering spatial dependencies of the predictors in spatial regression models. Statistical regression models are hence preferable.

The simple extrapolation (as a benchmark of the commonly used method today [14,15]) has a better performance from 2016 onwards, while the accuracy is unstable in early years of 2012–2015. This is because the extrapolation method is less effective for future projections under the emerging deployment of PV installation in early 2010s when the increasing trend and the growth rate is unstable. The high variability of sMPE and sMAPE values for extrapolation, however, suggest that its performance is less robust and reliable when the trend is unstable, particularly for new technologies, such as PV that witnessed unprecedent emergence. The latter is consistent with the study of Armstrong [42], who suggested that extrapolation has its vantage when there is limited information to do better forecasts and when a stable trend is assumed. When the trend is unstable, like in the case of PV, the extrapolation should be improved by carefully selecting and preparing data, for example, by adjusting the data for important events that occurred in the past [42] or, as we show, by using more refined statistical models instead. Such statistical models also allow the testing of different model specifications and, in contrast to extrapolation, also provide substantive explanations by using different predictive socio-technical variables.

Regarding the performance of spatially-explicit optimization model EXPANSE, we observed the lowest accuracy when projecting the installed PV capacity by using the least-cost scenario without policy. Accounting for the PV policy and the RES targets through scenario design, the overall accuracy performance increased moderately, but not at a disaggregated, spatial level in terms of errors per district. First, this is consistent with the previous studies [6–8], suggesting that energy system optimization models should improve their spatial resolution so that the inaccuracy hidden behind the high aggregation level is revealed. In this study, we observed a higher accuracy regarding the PV uptake at a national level in all models, but this was hiding a lower accuracy increase at a district level. Future research should thus investigate accuracy at a high spatial resolution and look for methods to increase the accuracy performance at a disaggregated level. Second, optimization models like EXPANSE prefer the cheapest technologies for capacity expansion. While the investment cost of solar PV in early 2010s were relatively high compared to other electricity generation technologies, EXPANSE under-projected PV installations. Situations, where such cost-optimization models underestimate new technologies, like PV and wind power, are commonly observed in retrospective assessments [31,37,50]. The situation can be improved if we apply the Modeling to Generate Alternatives (MGA) method to generate many near-optimal scenarios that could account for higher PV capacity diffusion with lower deviation from the real-world transition compared to least-cost-based scenarios [15,31,51]. Also, one could include differentiate between various actors and their incentives for PV installations. Besides modeling subsidies, the incentive to self-consumption on a household level with different price set-ups could also be included in the EXPANSE and other optimization models. Overall, discussions and comparisons in literature regarding statistial and mathematical modeling [52–54] suggest that mathematical modeling, like EXPANSE, could get insights from the statistical principles to better handle parametric sensitivities and model uncertainty.

In this study, the performance of statistical and optimization models is compared by adopting two accuracy indicators: sMPE and sMAPE. sMPE indicates the direction of the overall tendency of under-projection or over-projection by including the sign of the errors, though it is affected by the cancelation effects between positive and negative error values. To overcome this limitation, sMAPE is used as a complementary indicator to indicate the magnitude of errors. In the previous spatial study on PV projections by Müller and Trutnevyte [21], only one error RMSLE was used to compare the accuracy of different regression models in in-sample and out-of-sample evaluations. RMSLE provides similar information as sMAPE, while the logarithmic calculation makes the marginal differences among regression models even more curtailed. Hence RMSLE is not included in the study because it would better fit for quantities with different scales, or when the differences are evident. In our case, we demonstrated how useful it is to use several complementary indicators in line with literature [37].

In terms of limitations and future research perspectives, one could further improve the individual models. For example, this could involve increasing spatial resolution [19] and gathering and testing other socio-demographic and techno-economic predictors of the statistical models. In this study, we worked only with one-year ahead projections, which potentially leads to a high accuracy performance as compared to longer time horizons that are also of policy interest. Future work should therefore focus on different projection horizons, such as three or five-year-ahead of model fit, or even move to long-term technology diffusion modeling based on historical data. Then, different models could be compared on that basis and make projections for the future. To increase the accuracy of the scenarios generated by the EXPANSE model, the gap between the modeled cost-optimal scenario and the real-world data could be bridged by more hindcasting with the aim to find what model features better capture actual developments [31,32,37]. Features, such as different ways to model policy, to account for socio-economic drivers of PV installations, or to account for deviations from cost-optimality would be of interest to test first. Moreover, Modeling to Generate Alternatives and Monte Carlo methods could explore more plausible scenarios around the deterministic scenarios at a spatially-explicit level [31]. Finally, future work could also explore how to combine the strengths of different statistical and optimization modeling approaches, for example, by endogenizing new features in optimization models or by weighting models based on their retrospective performance.

3.6 Conclusion

In this study, we implemented and compared the accuracy of statistical, extrapolation, and optimization models to project new PV installations at a level of 143 districts in Switzerland in 2012–2020. We investigated a multiple linear regression model and various spatial regression models, based on sociodemographic and techno-economic predictors of PV growth. For optimization, the spatially-explicit EXPANSE model was used with and without various features to account for PV policy and renewable electricity generation target. Extrapolation was used as a benchmark for the simplest method commonly used today. By comparing the results of different approaches, we find that the statistical regression models overall outperform extrapolation and the optimization model EXPANSE. The spatial simultaneous autoregressive error model (SEM) slightly outperforms the multiple linear regression model (MLR) and the spatial simultaneous autoregressive lag model (SAR), indicating that the regression performance is improved by including spatial autocorrelation in errors. The performance of simple extrapolation is subject to the yearly volatility. The EXPANSE cost-optimization model has the tendency to underestimate the PV installations. The implementation of PV policies, like subsidies and feed-in-tariff revenues, and renewable electricity targets together in the EXPANSE model could increase the performance in a way that the PV uptake is promoted in some districts in the model. However, the accuracy improvement is less evident at a spatially-explicit district level, meaning that there is still substantial work to be done in bridging the gap between optimization modeling and real-world developments. For now, we conclude that statistical models are preferred over simple extrapolation or cost optimization for projecting future PV installations at a sub-national scale.

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4 Patterns in spatial diffusion of residential heat pumps in Switzerland

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4.1 Abstract

Diffusion of granular renewable energy technologies is known to be spatially heterogeneous within countries. We investigate patterns in the distribution of 319’341 residential buildings with heat pumps in 2’148 Swiss municipalities in 2021. Using stepwise regression and spatial statistical analysis, we identify influential technical and socio-economic factors of residential heat pump diffusion as well as associated spatial traits. The results show that residential heat pumps primarily have a higher diffusion level in sparsely populated areas where the shares of agricultural area and detached houses are higher, hinting at an urban-rural difference. Economic factors, like income and electricity price, have a limited impact on residential heat pump diffusion in Switzerland, except for unemployment rate that has a negative impact. Some Swiss cantons (states) have a distinctly higher or lower residential heat pump diffusion level than others, a phenomenon possibly induced by cantonal policies. The spatial diffusion of residential heat pumps also tends to be spatially clustered, not only within cantons but also at the inter-cantonal level, indicating spatial spillovers. These findings could help policymakers promote heat pump diffusion in a more effective and precise manner.

4.2 Introduction

Climate change is an urgent global issue nowadays [1]. To counter its threat, Switzerland has developed the Swiss Energy Strategy 2050 and recently also adopted the long-term goal of climate neutrality, aiming to decrease its energy consumption and deploy more renewable energy technologies [2,3]. Specifically, the Energy Strategy 2050 seeks to cut down by 63% the energy consumption in buildings, which accounts for around half of the country’s total energy consumption [4]. Among the options of reducing consumption in buildings, heat pumps are the key alternative to conventional low-temperature heating methods based on heating oil and natural gas to lower greenhouse gas emissions [5–9]. So far, adoption grew fast in Switzerland, from around 35’000 heat pump installations in 1990 to 378’000 in 2021 [10], but the current number is far from what is needed for the goals of the Energy Strategy 2050 and ultimately climate neutrality. Similar to other granular renewable energy technologies, heat pump diffusion is subject to various influential factors, such as sociodemographic, technoeconomic and housing characteristics of the adopters [11,12]. Understanding which influential factors underpin heat pump diffusion is of critical importance, as policymakers can then consider local and contextual specificities to elaborate better policies facilitating heat pump diffusion [11,13]. In particular, some researchers argue that spatial differentiation occurs in technology growth [14], which is supported by numerous studies on the diffusion of granular renewable energy technologies like solar photovoltaic systems and bioenergy [11–13,15–18]. Hence, comprehending the drivers of spatial diffusion can especially inform how the diffusion process can be accelerated.

Current studies that explored the influential factors of the diffusion of granular renewable energy technologies are abundant but mainly focus on solar photovoltaic systems. Empirical investigations in many developed countries like Germany [16,19], Switzerland [12], the United Kingdom [15,20–22] and the United States [23] have revealed that the diffusion of solar photovoltaic systems can be affected by many factors, such as income, age and education level. Findings based on the case of one country do not necessarily hold true for another country, despite some possible common traits. For example, education level is deemed to be positively related to the diffusion of solar photovoltaic systems in Germany and the United Kingdom [15,16,20], whereas the role of income is inconsistent from case to case [12,16,19,20]. Only a few studies conducted outside of Switzerland have tried to identify the influential factors of heat pump diffusion with logistic or agent-based models for prediction purposes [24–26]. With so little work on heat pumps, findings on the influential factors of the diffusion of solar photovoltaic systems might be solely applicable to these systems and might not be transferable to heat pumps. The existing findings on the influential factors of heat pump diffusion might not be transferable to Switzerland, either. Furthermore, studies having investigated the spatial diffusion of granular renewable energy technologies also mainly concentrate on solar photovoltaic systems. These studies were able to show that the diffusion of solar photovoltaic systems is spatially heterogeneous and the reasons are manifold, from characteristics of the owners to technical potential and regional specificities [16,17,20]. The diffusion of solar photovoltaic systems in one region was also found to cross regional boundaries and thereby create spatial spillovers [19,21,22,27,28]. By contrast, no research has integrated the spatial dimension when studying heat pump diffusion and this is the scope of the current study.

In this study, we present an empirical investigation of the spatial diffusion of 319’341 residential heat pumps in 2021 in the 2’148 municipalities of Switzerland. The aims of this study are (1) to identify the influential factors of residential heat pump diffusion out of 15 sociodemographic, technoeconomic and housing characteristics, (2) to verify if residential heat pump diffusion is spatially heterogeneous and (3) if spatial spillovers exist during residential heat pump diffusion in Switzerland. The reason for considering residential buildings only is based on the assumption that residential heat pumps obey different diffusion mechanisms from industrial or commercial heat pumps. Industrial heating temperatures are also often distinctly higher than residential heating temperatures. Current heat pump technologies can only partially satisfy low-temperature industrial heating demand, which makes heat pump a mediocre option for decarbonising the industrial sector [29].

The study is divided into two steps: regression analysis and spatial analysis. First, we use stepwise regressions to detect relevant influential factors of heat pump diffusion via two indicators: number of residential buildings heated by heat pumps per 1’000 buildings and per 1’000 inhabitants. We also analyse if there are any cantonal differences in terms of heat pump diffusion. Second, we identify statistically significant hot and cold spots of heat pump diffusion for all Switzerland and within Swiss cantons (states) and analyse what distinguishes hot spots from cold spots in terms of sociodemographic, technoeconomic and housing characteristics. This step also serves to verify if spatial spillovers exist in heat pump diffusion in Switzerland. Finally, we summarise the key findings of our empirical analysis, its limitations and future research needs.

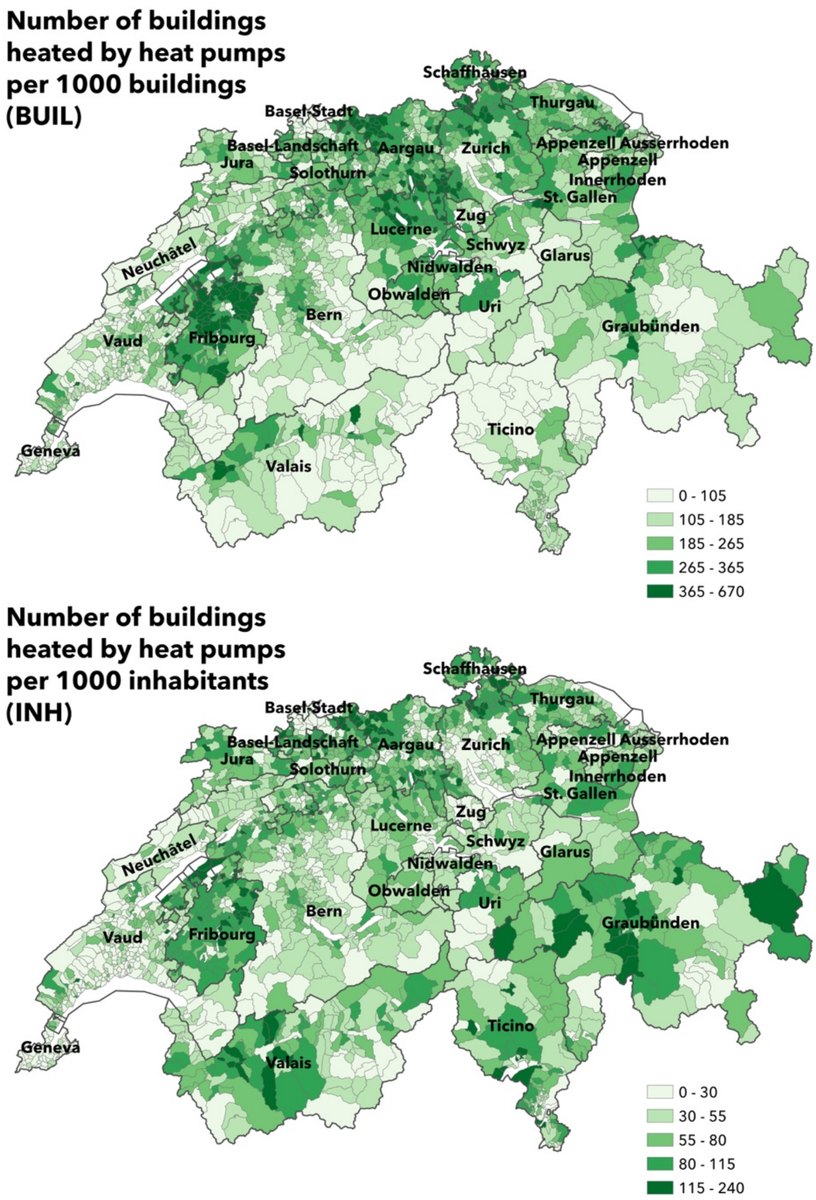
4.3 Data and methodology

4.3.1 Data

4.3.1.1 Heat pumps

To understand residential heat pump diffusion at the municipal level in Switzerland, we use two indicators: number of residential buildings heated by heat pumps per 1’000 buildings (BUIL) and per 1’000 inhabitants (INH). Both indicators will be referred to as heat pump diffusion below for convenience. This study only includes residential buildings, that is, buildings with at least one permanent dwelling. Buildings like nursing homes and dormitories for students and workers are also considered residential, but not hotels, hospitals nor prisons. The dataset of heat pumps comes from the Swiss Federal Register of Buildings and Dwellings (RBD), which is provided by the Swiss Federal Statistical Office [30]. The RBD database contains details of all types of buildings in Switzerland, such as address, construction year and heating type for space heating and domestic hot water production. The provider of the RBD database does not specify how complete the database is. However, the database registered a total of around 1.7 million buildings in 2021, which represents approximatively 95.8% of the official number of buildings published by the Swiss Federal Statistical Office [31]. Thus, the RBD database covers a considerable share of Swiss buildings for our investigation on heat pump diffusion in Switzerland. The RBD database only provides the number of buildings with at least one heat pump satisfying primary or secondary heating services, instead of directly specifying the number of heat pump installations. Hence the indicators used in this study count the number of buildings heated by heat pumps and not the number of heat pump installations.

The RBD database registers 319’341 buildings using heat pumps to satisfy their heating services exclusively or partially in 2021. A building is considered heated by heat pumps when heat pumps serve as either its primary or secondary heating source. Heat pumps used for space heating or domestic hot water production are not differentiated. The buildings are aggregated to the level of 2’148 Swiss municipalities using the geographic coordinates of these buildings. Municipalities are the collection unit for many sociodemographic, technoeconomic and housing statistics (see Section 4.3.1.2). Given that municipalities are the smallest independent administrative divisions in Switzerland [17,18], an aggregation at the municipal level offers a high resolution for the analyses and thus can potentially accentuate how heat pump diffusion is sensible to spatial conditions. Figure 4-1 depicts heat pump diffusion in every municipality with respect to the two indicators of interest. Both indicators mainly have



high values in Fribourg and German-speaking cantons (north-east), whereas INH has also some high values in western Valais, Ticino and Graubünden.

Figure 4-1. Number of residential buildings heated by heat pumps in 2’148 Swiss municipalities in 2021. The grey lines show municipal boundaries and the black lines show cantonal boundaries. The visualisation is based on natural breaks [32].

4.3.1.2 Determinants of heat pump diffusion

To understand how heat pump diffusion is driven by various influential factors in Switzerland, 15 sociodemographic, technoeconomic and housing characteristics are selected as potential determinants of BUIL and INH. Table 4-1 shows all 15 determinants with a description and information on data source. Most determinants are selected from previous studies as they have been shown to be important for other granular renewable energy technologies, e.g. income [12,15,16,18–20,22,24,27,33–35], age [11,16,24,35–38], education level [15,16,20,21,23–25,34], settlement area [12,13,17,18,34,39], homeownership [15,25,27,33,40], population density [12,15,19,20]. Other determinants, such as share of protected historical buildings, are added specifically because they could be important for heat pump diffusion. The data of the determinants from Table 4-1 are all publicly available [41–44]. Most determinants are available at the municipal level. Whereas the determinant of tertiary degree holder is available at the district level, owned dwellings, unemployment rate and historical buildings are only available at cantonal level. Since the heat pump data are updated to 2021, data of most determinants are linearly extrapolated to 2021 as they are not directly available for the year 2021. However, data that are aggregated over several years, e.g. agricultural area, or rarely updated, e.g. historical buildings, are directly used without undergoing the linear extrapolation.

Table 4-1. Overview of the 15 determinants of heat pump diffusion used in the analyses. The data of the determinants come from the Swiss Federal Office of Energy [41], the Swiss Political Atlas [42], the Swiss Statistical Atlas [43] and the Swiss Federal Electricity Commission [44].

Sociodemographic determinants	**Unit**	**Description**	**Spatial resolution**	**Year**
Agricultural area	%	Share of agricultural area. The share of agricultural area has been found important for the diffusion of other granular renewable energy technologies in Switzerland [12,17,18].	Municipality	2013/2018
Average household size	inh./household	–	Municipality	2012–2020
Average net income	CHF/capita	–	Municipality	2010–2018
CO_2 Act referendum	%	Share of voters who voted in 2021 in favour of the CO_2 Act that aims to reduce Switzerland's greenhouse gas emissions [45]. This determinant is a proxy for environmental attitudes.	Municipality	2021
Green voters	%	Share of voters who voted for Social Democratic Party, Green Party, Green Liberal Party and Evangelical People's Party during the 2019 Swiss National Council election. This determinant is a proxy for environmental attitudes.	Municipality	2019
Population density	inh./km^2	Population density reflects the urban-rural divide.	Municipality	2008–2021
Total dependency ratio	–	Inhabitants under 20 or over 64 years old divided per 100 inhabitants between 20 and 64.	Municipality	2010–2020
Unproductive area	%	Share of unproductive area. This determinant mostly distinguishes alpine or unbuilt areas in Switzerland [12,17].	Municipality	2013/2018
Tertiary degree holder	%	Share of inhabitants over 24 having a tertiary degree. This determinant measures education attainment.	District	2016/2018
Owned dwellings	%	Share of owned dwellings.	Canton	2000–2020
Unemployment rate	%	Share of the unemployed in the active population.	Canton	2010–2020
Technoeconomic determinants	**Unit**	**Description**	**Spatial resolution**	**Year**
Average electricity price	Rp./kWh	Electricity price reflects the price of heat from heat pumps.	Municipality	2009–2021
Energy City label	–	This determinant shows whether a municipality has the Energy City label or not, indicating whether the municipality pursues a sustainable energy policy.	Municipality	–
Housing characteristics	**Unit**	**Description**	**Spatial resolution**	**Year**
Detached houses	%	Share of detached houses.	Municipality	2009–2020
Historical buildings	%	Share of protected historical buildings. Changes made to the heating method of protected historical buildings are strictly regulated in Switzerland.	Canton	2016

To quantify people's environmental attitudes, we choose two proxies: (1) share of voters approving the Swiss referendum of CO_2 Act on 13 June 2021 [45], and (2) share of voters for Social Democratic Party, Green Party, Green Liberal Party and Evangelical People's Party as these parties are the comparatively closest to environmental topics [12,46]. The share of protected historical buildings is added to see if this determinant constitutes an obstacle to heat pump diffusion. Protected historical buildings comprise many building types but the exact share is not specified for every type. To render the data more representative, the share of religious buildings is subtracted from the total as religious buildings represent a considerable share in some cantons. The electricity price is included in the analysis to examine if changes in electricity price influence heat pump diffusion as heat pumps operate on electricity. Swiss electricity providers propose different tariffs to different consumers based on electricity consumption. In this study, households with an average annual electricity demand of 4.5 MWh, which typically correspond to a five-room dwelling with electric cooker and tumble dryer and no electric water heater, are chosen as a proxy [44].

4.3.2 Methodology

4.3.2.1 Stepwise regression

To understand how heat pump diffusion in terms of BUIL and INH could be predicted by the 15 determinants from Table 4-1, we conduct stepwise regressions to select the most relevant determinants. Stepwise regressions select the predictive variables that contribute most to the F-statistic of a model and only keep the predictive variables with a p-value within a certain range (usually $p \leq 0.05$) [47]. Both indicators of BUIL and INH undergo a $\ln(y+1)$ transformation to ease the skewness of the original data, and the transformed indicators are then put into the regressions as response variables. All determinants serve as predictive variables of the regressions and are standardised due to different scales. The only exception is Energy City label, which is a categorical determinant with binary values of 1 (yes) and 0 (no) and hence does not undergo any transformation. In the second step, 26 Swiss cantons are put into stepwise regressions as dummy variables to extract a potential role of cantonal heat pump policies. As the 15 determinants are not selected using any theory that could explain causality, the determinants selected by the stepwise regressions do not necessarily have a causal relationship with the response variables of BUIL and INH [17]. Hence, in our study, the selected predictive variables can merely indicate the determinants that could be used to predict heat pump diffusion.

4.3.2.2 Spatial analysis

To investigate whether heat pump diffusion is also spatially clustered in Switzerland, we first perform Optimised Hot Spot Analysis in ArcGIS Pro [48] to achieve two goals. First, we want to identify statistically significant clusters of neighbouring municipalities with a high or low level of heat pump diffusion respectively as hot spots and cold spots. Second, we want to examine if there are any spatial spillovers in the diffusion process of heat pumps in Switzerland across municipal boundaries, following the example of existing literature [17]. Optimised Hot Spot Analysis automatically determines the threshold distance within which two features are considered neighbours [49]. The threshold distance that Optimised Hot Spot Analysis calculates for the Swiss municipalities is 25.56 km. Moran's I is then calculated to quantify the spatial autocorrelation of BUIL and INH. Moran's I is typically used to detect spatial autocorrelation, which constitutes a quantitative method of verifying if heat pump diffusion is spatially clustered in Switzerland. Optimised Hot Spot Analysis is then complemented by analysis of variance (ANOVA) to reveal what distinguishes hot spots from cold spots in terms of statistically significant differences in the values of BUIL and INH as well as the determinants. Both hot spots and cold spots are respectively compared to municipalities that are categorised neither as hot spots nor as cold spots, in other words, municipalities with randomly distributed levels of heat pump diffusion around the average. In the second step, to verify the existence of spatial spillovers at a higher spatial resolution, Optimised Hot Spot Analysis is performed individually on cantons with at least 30 municipalities as Optimised Hot Spot Analysis requires at least 30 features to function. A threshold distance specific to each canton can better detect hot and cold spots within cantonal boundaries since municipalities take different sizes from canton to canton. ANOVA tests are additionally performed individually on the cantons with at least 30 municipalities to understand the differences of the indicators and the determinants between hot spots and cold spots.

4.4 Results

4.4.1 Stepwise regressions

The variance inflation factors show that none of the determinants used is seriously correlated with one another (see Table 5-2 and Table 5-3 in Appendix C), indicating that the regression results are clear of the effects of multicollinearity. Stepwise regression on the BUIL variable (Table 4-2) finds eleven determinants to have a statistically significant predictive power, explaining approximately 36.8% of total variance. Of the eleven determinants, unemployment rate influences BUIL the most with negative effects. The other most important determinants include share of agricultural area (positive effects), share of detached houses (positive effects) and share of unproductive area (negative effects). These four determinants account for 30.1% of the total explained variance. Passing on to less important determinants, average electricity price, share of owned dwellings, average household size and share of green voters have similar influential power on BUIL, where only average electricity price is negatively related to BUIL. Low influential determinants include total dependency ratio, average net income and share of protected historical buildings, where only average net income has positive effects on BUIL. When cantons are added as dummy variables into the regression, the total explained variance increases to 44.5% from 36.8% (Table 4-3). The first three determinants selected by the regression remain share of agricultural area, share of detached houses and unemployment rate, as in the previous regression without cantons. Then, cantons start to contribute to the prediction power of the regression model. Cantons of Aargau, Fribourg, Zurich and Schaffhausen have positive effects on BUIL, while cantons of Appenzell Ausserrhoden, Schwyz, Geneva, Basel-Stadt, Neuchâtel and Vaud have negative effects.

Table 4-2. Stepwise regression results with the number of residential buildings heated by heat pumps per 1’000 buildings (BUIL) as response variable.

R^2	**0.096**	**0.195**	**0.269**	**0.301**	**0.326**	**0.337**	**0.345**	**0.355**	**0.364**	**0.367**	**0.368**
Adjusted R^2	**0.096**	**0.194**	**0.268**	**0.299**	**0.324**	**0.335**	**0.343**	**0.352**	**0.361**	**0.364**	**0.365**
***F*-statistic**	**228.2**	**260.2**	**263.4**	**230.2**	**207.1**	**181.3**	**161.4**	**146.9**	**136.0**	**123.7**	**113.1**
Regression constant	**5.168*** **	**5.168*** **	**5.168*** **	**5.168*** **	**5.168*** **	**5.168*** **	**5.168*** **	**5.168*** **	**5.168*** **	**5.168*** **	**5.168*** **
Agricultural area	0.220***	0.223***	0.235***	0.172***	0.172***	0.170***	0.176***	0.138***	0.147***	0.149***	0.158***
Detached houses		0.223***	0.269***	0.249***	0.232***	0.244***	0.223***	0.204***	0.190***	0.185***	0.184***
Unemployment rate			–0.199***	–0.219***	–0.218***	–0.220***	–0.197***	–0.205***	–0.234***	–0.234***	–0.235***
Unproductive area				–0.145***	–0.158***	–0.148***	–0.171***	–0.171***	–0.149***	–0.148***	–0.146***
Average electricity price					–0.115***	–0.097***	–0.104***	–0.092***	–0.100***	–0.096***	–0.088***
Total dependency ratio						–0.077***	–0.072***	–0.070***	–0.066***	–0.066***	–0.067***
Owned dwellings							0.076***	0.091***	0.110***	0.118***	0.106***
Average household size								0.085***	0.095***	0.093***	0.094***
Green voters									0.086***	0.085***	0.096***
Average net income										0.037**	0.037**
Historical buildings											–0.035*

*Statistical significance codes: *** p ≤ 0.001, ** p ≤ 0.01, * p ≤ 0.5.*

Table 4-3. Stepwise regression results with the number of residential buildings heated by heat pumps per 1'000 buildings (BUIL) and per 1'000 inhabitants (INH) as response variables and with cantons as dummy variables.

BUIL		**INH**	
R^2	**0.445**	**R^2**	**0.575**
Adjusted R^2	**0.440**	**Adjusted R^2**	**0.570**
***F*-statistic**	**81.2**	***F*-statistic**	**124.8**
Regression constant	**5.143*** **	**Regression constant**	**3.756*** **
Agricultural area	0.149***	Population density	–0.159***
Detached houses	0.151***	Detached houses	0.300***
Unemployment rate	–0.180***	Unemployment rate	–0.281***
Canton of Aargau	0.427***	*Canton of Fribourg*	0.559***
Unproductive area	–0.123***	*Canton of Aargau*	0.488***
Canton of Fribourg	0.474***	Agricultural area	0.185***
Canton of Zurich	0.255***	Energy City	–0.126***
Historical buildings	–0.096***	*Canton of Schwyz*	–0.344***
Average household size	0.116***	*Canton of Appenzell Ausserrhoden*	–0.380***
Green voters	0.041	*Canton of Uri*	–0.236*
Canton of Appenzell Ausserrhoden	–0.595***	*Canton of Ticino*	0.521***
Canton of Schwyz	–0.254*	*Canton of Zurich*	0.274***
Total dependency rate	–0.050***	*Canton of Jura*	0.641***
Average net income	0.036**	*Canton of Valais*	0.446***
Canton of Geneva	–0.627***	*Canton of Schaffhausen*	0.463***
Canton of Basel-Stadt	–0.959**	Average net income	0.057***
Canton of Neuchâtel	–0.424***	Tertiary degree holder	–0.041**
Canton of Vaud	–0.253***	*Canton of Graubünden*	0.202***
CO_2 Act referendum	0.065***	*Canton of Solothurn*	0.153**
Canton of Schaffhausen	0.244*	Total dependency ratio	0.032**
Population density	–0.032*	*Canton of Lucerne*	0.170**
		Canton of Glarus	–0.570*
		Canton of Geneva	–0.167*

*Statistical significance codes: *** p ≤ 0.001, ** p ≤ 0.01, * p ≤ 0.5.*

The stepwise regression for the INH variable explains up to 50.3% of the total variance (Table 4-4). Out of nine statistically significant determinants, share of detached houses turns out to be the most important one. The first three determinants of the regression, i.e. population density, share of detached houses and unemployment rate, are responsible for 45.2% of the total variance explained. The other six determinants influence the prediction power of the regression much less. From the strongest to the weakest, the determinants that positively influence INH are share of detached houses, share of agricultural area, share of owned dwellings and average net income, and those that negatively influence

INH are unemployment rate, population density, Energy City label, tertiary degree holder and average electricity price. When cantons are added into the regression model as dummy variables, the prediction power of the regression model only slightly increases from 50.3% to 57.5% (Table 4-3). The first three determinants selected by the regression remain the same as in the regression without cantons: population density, share of detached houses and unemployment rate. The cantons that are positively related to INH are Fribourg, Aargau, Ticino, Zurich, Jura, Valais, Schaffhausen, Graubünden, Solothurn and Lucerne, whereas INH is negatively impacted by the cantons of Schwyz, Appenzell Ausserrhoden, Uri, Glarus and Geneva. Cantons that appear in the regression results of both BUIL and INH have the same effects on the indicators.

Table 4-4. Stepwise regression results with the number of residential buildings heated by heat pumps per 1'000 inhabitants (INH) as response variable.

R^2	**0.222**	**0.379**	**0.452**	**0.474**	**0.493**	**0.495**	**0.498**	**0.501**	**0.503**
Adjusted R^2	**0.222**	**0.378**	**0.452**	**0.473**	**0.491**	**0.494**	**0.496**	**0.499**	**0.500**
***F*-statistic**	**613.2**	**653.9**	**590.2**	**482.2**	**415.9**	**350.4**	**303.2**	**268.5**	**240.0**
Regression constant	**3.906*****	**3.906*****	**3.906*****	**3.906*****	**3.906*****	**3.928*****	**3.928*****	**3.927*****	**3.929*****
Population density	–0.342***	–0.296***	–0.261***	–0.219***	–0.190***	–0.180***	–0.183***	–0.171***	–0.173***
Detached houses		0.290***	0.343***	0.355***	0.337***	0.336***	0.328***	0.333***	0.329***
Unemployment rate			–0.205***	–0.220***	–0.187***	–0.191***	–0.191***	–0.185***	–0.184***
Agricultural area				0.114***	0.147***	0.144***	0.144***	0.147***	0.148***
Owned dwellings					0.114***	0.114***	0.122***	0.103***	0.103***
Energy City						–0.094***	–0.094***	–0.090***	–0.098***
Average net income							0.037**	0.052***	0.049***
Tertiary degree holder								–0.053***	–0.054***
Average electricity price									–0.029*

*Statistical significance codes: *** p ≤ 0.001, ** p ≤ 0.01, * p ≤ 0.5.*

4.4.2 Spatial statistical analysis

4.4.2.1 Hot spot analysis at the national level

The hot spot analysis confirms that heat pump diffusion is not evenly distributed in Switzerland (Figure 4-2). In general, the hot spots of BUIL are concentrated in Fribourg and several northern German-speaking cantons, while the cold spots are concentrated in French-speaking cantons (west) and Alpine cantons (south). The hot spots for INH share a similar pattern to BUIL. However, Basel-Stadt turns out to be a hot spot of INH whereas the canton is a cold spot of BUIL. Other hot spots emerge in western Valais, western Ticino and western Graubünden. The three French-speaking cantons of Geneva, Vaud and Neuchâtel, together with eastern Bern and eastern Valais, remain a large area of cold spots as for BUIL. Overall, the areas of hot and cold spots roughly follow the shape of the Swiss cantons, indicating that there may be an effect of cantonal policies in heat pump diffusion. The hot and cold spots in terms of cantons also correspond to the regression results listed in Table 4-3. Moran's I shows that both BUIL and INH tend to be spatially clustered, with a value of 0.401 for BUIL and 0.291 for INH (for both indicators: $p < 0.001$, threshold distance around 20.51 km).

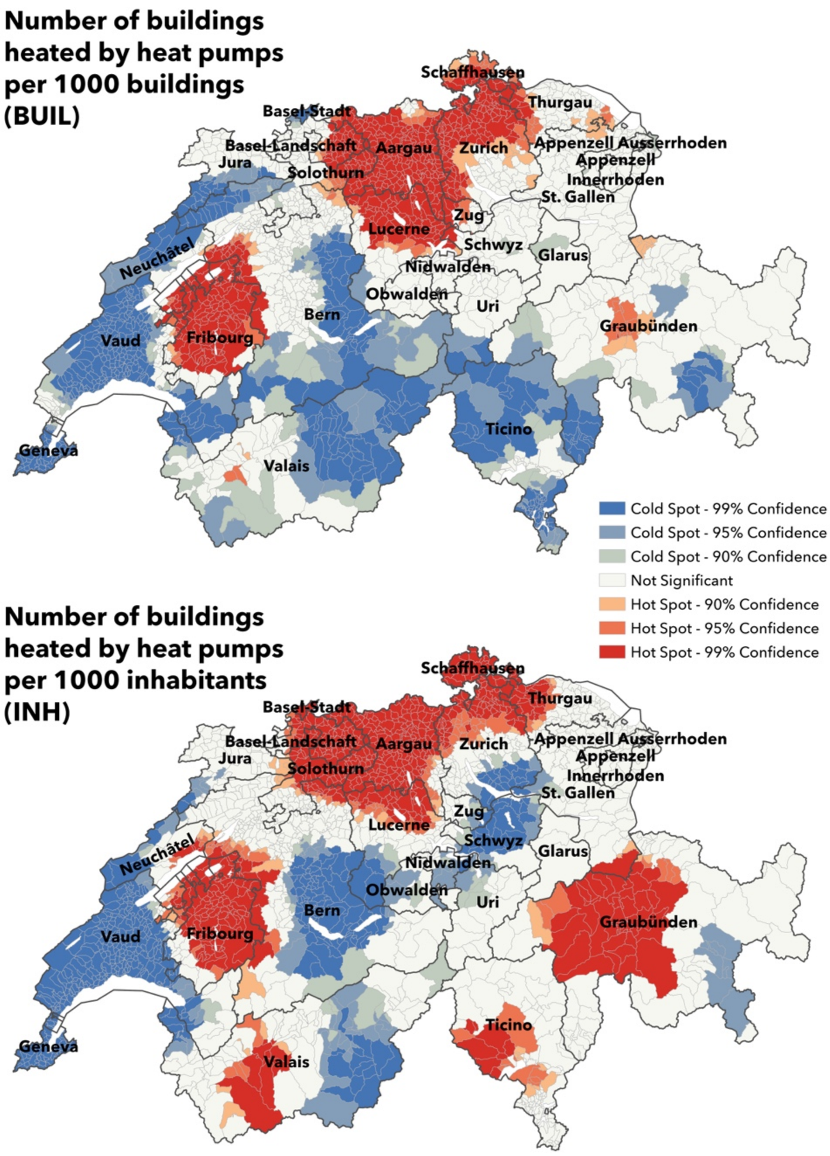


Figure 4-2. Hot and cold spots of heat pump diffusion at the national level in Switzerland. The hot and cold spots are calculated with Optimised Hot Spot Analysis in ArcGIS [48], with a threshold distance of 25.56 km. The grey lines show municipal boundaries and the black lines show cantonal boundaries.

Table 4-5 shows the results of the ANOVA tests which highlight the differences between hot or cold spots and the other municipalities that are neither hot nor cold spots. Naturally, hot spots have a significantly higher level of heat pump diffusion in terms of both indicators. For BUIL, hot spots have higher share of agricultural area, lower total dependency ratio, lower share of unproductive area, lower share of owned dwellings, higher unemployment rate, lower electricity prices, higher share of detached houses, and higher share of protected historical buildings than municipalities that are neither hot nor cold spots. In contrast, cold spots have lower share of agricultural area, higher share of unproductive area, lower share of owned dwellings, higher unemployment rate, lower share of detached houses, and higher share of protected historical buildings than municipalities that are neither hot nor cold spots. As for other statistically significant determinants, including share of voters who voted in favour of the CO_2 Act, share of green voters and share of tertiary degree holders, hot and cold spots diverge relatively similar from municipalities that are neither hot nor cold spots. Average net income and population density are statistically unsignificant for both hot spots and cold spots.

Table 4-5. Results of ANOVA tests comparing respectively hot spots and cold spots to other municipalities. Note that hot and cold spots only include municipalities with a confidence level of at least 95%. The column of Other shows the mean values of the indicators and the determinants. While the columns of Hot spots and Cold spots show the mean differences between hot/cold spots and municipalities that are neither hot nor cold spots.

	Unit	**BUIL**			**INH**		
		Hot spots	Other	Cold spots	Hot spots	Other	Cold spots
Municipalities	–	663	905	580	761	834	553
Indicators							
BUIL	HP[a]/1'000 buil.	102.84***	198.56	–76.32***	81.65***	191.49	–41.63***
INH	HP/1'000 inh.	20.16***	58.99	–19.64***	21.51***	56.95	–18.10***
Sociodemographic determinants							
Agricultural area	%	4.5***	45.1	–6.0***	3.0**	42.5	5.4***
Average household size	inh./household	0.07***	2.26	0.03	0.05***	2.25	0.11***
Average net income	CHF/capita	1'312	38'194	2'368	1'469*	37'204	5'878***
CO_2 Act referendum	%	1.4*	38.8	3.0***	0.7	38.9	3.5***
Green voters	%	4.5***	30.7	4.1***	4.3***	30.1	6.2***
Population density	inh./km^2	45.8	409.5	92.3	22.3	414.3	102.1
Total dependency ratio	–	–4.34***	69.63	–0.70	–3.07***	69.78	–2.29***
Unproductive area	%	–5.2***	7.2	3.4***	–5.2***	9.1	–2.7**
Tertiary degree holder	%	1.0**	29.3	2.0***	1.2***	28.3	5.8***
Owned dwellings	%	–1.2**	40.4	–5.0***	0.0	40.6	–7.3***
Unemployment rate	%	0.3***	2.6	0.9***	0.1***	2.7	0.8***
Technoeconomic determinants							
Average electricity price	Rp./kWh	–2.07***	21.61	0.08	–1.39***	21.54	–0.17
Housing characteristics							
Detached houses	%	4.4***	58.6	–2.4**	4.7***	59.0	–5.3***
Historical buildings	%	0.8***	5.4	1.8***	1.1***	4.9	3.2***

*Statistical significance codes: *** $p \leq 0.001$, ** $p \leq 0.01$, * $p \leq 0.5$.*
[a] *HP stands for number of buildings heated by heat pumps.*

For INH, hot spots have higher share of agricultural area, higher share of green voters, lower share of unproductive area, higher share of tertiary degree holders, higher unemployment rate, lower electricity prices, higher share of detached houses and higher share of protected historical buildings than municipalities that are neither hot nor cold spots. While cold spots have higher share of agricultural area, higher average net income, higher share of positive voters for the CO_2 Act, higher share of green voters, lower share of unproductive area, higher share of tertiary degree holders, lower share of owned dwellings, lower share of detached houses, and higher share of protected historical buildings than municipalities that are neither hot nor cold spots. Average household size and total dependency ratio have a limited influence on INH, with hot and cold spots showing relatively small differences when compared to municipalities that are neither hot nor cold spots. Similar to BUIL, population density is statistically unsignificant for INH.

4.4.2.2 Hot spot analysis at the national level

In order to analyse spatial patterns by eliminating potential effects of cantons and cantonal policies, Figure 4-3 depicts the hot and cold spots in all 16 Swiss cantons with at least 30 municipalities. Most cantons contain hot and cold spots at the same time with respect to both indicators, indicating that heat pump diffusion is spatially heterogeneous not only at the national level but also within cantons. Even cantons whose municipalities are almost all hot or cold spots at the national level, e.g. Aargau or Vaud (Figure 4-2), own hot and cold spots within their boundaries. But some cantons almost do not show any considerable hot nor cold spots for both indicators, such as Thurgau, St. Gallen and Schwyz. For both indicators, hot spots in north-eastern Vaud, northern Bern, eastern Basel-Landschaft, northern Lucerne and northern Zurich are all concentrated around cantonal boundaries. The results of the ANOVA tests performed individually on each canton shows that hot-spot municipalities have in general higher BUIL and INH values than cold-spot municipalities in most cantons with at least 30 municipalities (Table 5-4 in Appendix D). The negative effects of population density and the positive effects of share of detached houses are observed in several cantons like Zurich and Aargau. Education level has nevertheless mixed effects, with positive effects observed in Lucerne and negative effects in Basel-Landschaft and Fribourg. The other determinants are mostly statistically unsignificant.

4.5 Discussion

Our investigation reveals that the spatial diffusion of heat pumps in Switzerland can be predicted by several sociodemographic, technoeconomic and housing characteristics. Share of agricultural area, share of detached houses and unemployment rate are among the most influential determinants for both indicators. They all influence heat pump diffusion in the same manner: apart from unemployment rate which has negative effects, the other two determinants both positively influence heat pump diffusion. The positive influence of share of agricultural area and share of detached houses insinuate that rural municipalities with heavier agricultural activities have a higher heat pump diffusion level. Interestingly, rural areas have already been deemed to have positive effects on the diffusion of granular renewable energy technologies in Switzerland [12,13,17] and elsewhere [34,39], such as solar photovoltaic systems and microgeneration heat technologies. One possible reason why heat pumps are better adopted in rural areas is that the space required by heat pump installations can be scarce in urban environments [39]. This finding hints to the fact that policymakers could pay more attention to rural areas to promote heat pump diffusion. The regression results also show that population density has relatively strong negative effects on heat pump diffusion, which also supports the idea that rural areas are a better niche for heat pumps than densely populated urban areas. While the ANOVA tests show that population density has no statistically significant differences between hot or cold spots and other municipalities in terms of both indicators. Population density has thus probably a strong influence on heat pump diffusion when considered with other determinants, like share of detached houses and share of agricultural area, but is not a decisive determinant alone.

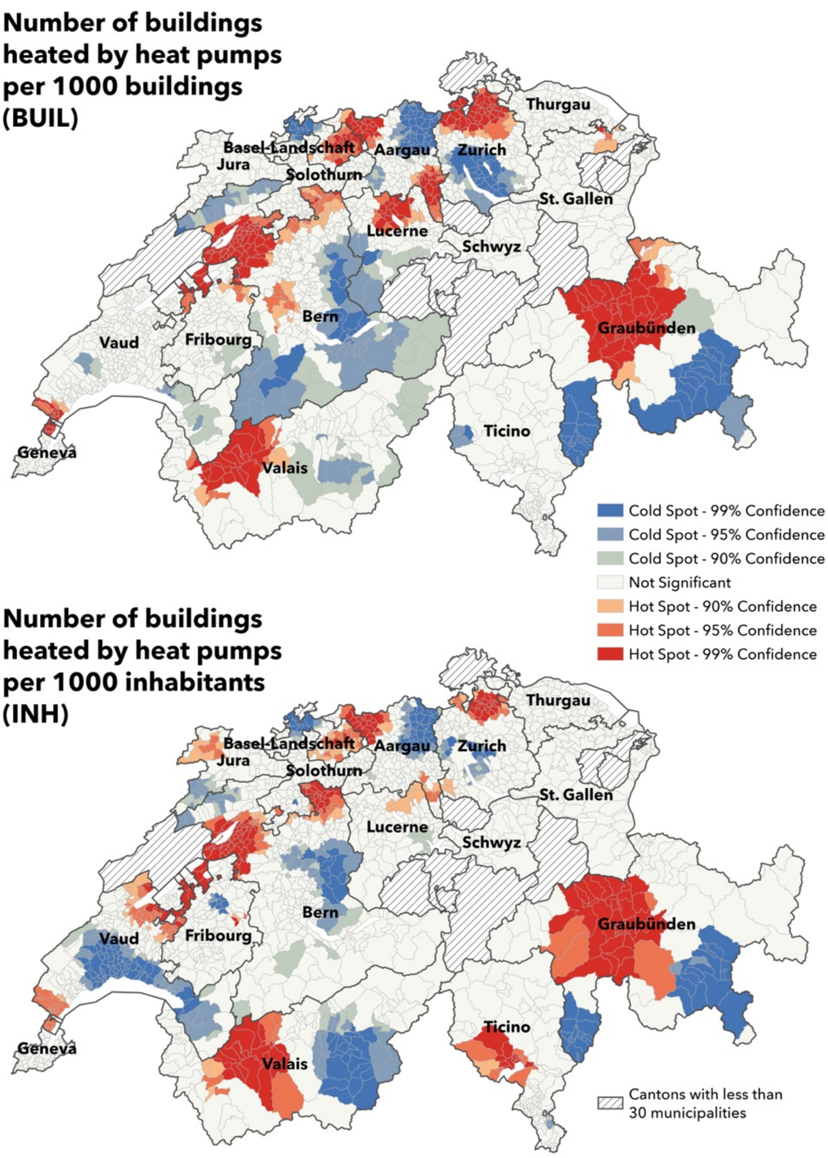


Figure 4-3. Hot and cold spots of heat pump diffusion in Swiss cantons with at least 30 municipalities. The hot and cold spots are calculated with Optimised Hot Spot Analysis in ArcGIS [48], with a threshold distance specific to each canton. As the Optimised Hot Spot Analysis requires at least 30 features to function, cantons with less than 30 municipalities are not analysed (black stripes). The grey lines show municipal boundaries and the black lines show cantonal boundaries.

In terms of other determinants, share of unproductive area has a fairly strong negative influence on BUIL according to the regression results. This is because there are plentiful uninhabitable mountains, lakes and glaciers in Switzerland [12]. The other determinants selected by the stepwise regressions only explain a small part of the total variance and have a much smaller influence on the indicators than share of agricultural area, share of detached houses and unemployment rate. It is nevertheless interesting to see that determinants related to age and environmental attitudes (CO_2 Act referendum and green voters) do not have any considerably decisive impact on the indicators, in accordance with past findings on solar photovoltaic systems [12,16,27]. However, it is thought-provoking that income turns out to be able to predict heat pump diffusion in Switzerland only very slightly and that it is not among the most influential factors. In previous research, income has been found inconclusive on the diffusion of granular renewable energy technologies: while some studies find income to have positive effects [15,33,34], others find otherwise [12,20,24]. The findings on the relation between income and heat pump diffusion are likely a specific case of Switzerland. Electricity price and hence heat price with heat pumps were not found influential, either. However, to some extent, the role of wealth is possibly captured by unemployment rate. Numerous studies have confirmed that upfront cost is a major obstacle to the diffusion of energy innovations [50–52], and this could explain why unemployment rate has a negative impact on heat pump diffusion, because the unemployed might be less able to invest in heat pumps due to high upfront and installation costs than people with a stable income. However, data of unemployment rate are only available at the cantonal level and hence might not be representative of the real prediction power of unemployment rate at the municipal level. The effects of unemployment rate thus need to be taken cautiously.

Our spatial analysis further confirms that heat pump diffusion is spatially heterogeneous in Switzerland, with large concentrations of hot and cold spots throughout the country. Apart from the common zones of hot spots shared by both BUIL and INH indicators, i.e. Fribourg and northern German-speaking cantons, INH has additionally some large aggregations of hot spots in western Valais, western Ticino and western Graubünden. The spatial analysis is able to confirm the notable influence of cantons on heat pump diffusion, especially in Geneva, Vaud, Fribourg and Aargau where almost the whole canton comes out as hot or cold spots. German-speaking cantons have a higher level of heat pump diffusion than French-speaking cantons based on the heat maps and the hot spot analysis. This is also consistent with the results of the stepwise regressions with cantons as dummy variables, where some cantons play a more important role than the determinants. The results highlight that some cantons have a distinctly higher or lower heat pump diffusion level than others. This is possibly due to the role of cantonal policies to promote heat pump diffusion, but there is no good-quality database of cantonal policies to integrate this information in our analyses.

Furthermore, our spatial analysis shows that spatial spillovers exist and not only within but also across cantonal boundaries, similar to the spillover effects observed for solar photovoltaic systems in Germany [16,40] and Switzerland [12,53]. Some cantons contain major hot or cold spots in the nationwide hot spot analysis, possibly reflecting the role of cantonal policies as mentioned before. However, within these cantons, heat pump diffusion does not show any spatial clusters, e.g. Thurgau and St. Gallen, indicating that heat pump diffusion could tend to be spatially homogeneous in these cantons. Yet, the presence of hot and cold spots within cantonal boundaries also indicates that there are more local spillover factors at play. Hence, although not all cantons are included when the hot spot analysis is performed individually on Swiss cantons, it is reasonable to infer that spatial spillovers more or less exist in the cantons with less than 30 municipalities as well, either within or beyond cantonal boundaries.

Our analyses have limitations that can be handled in future research. First, the regression models used in our study are solely linear regressions, but the response variables used in the regressions turn out to be spatially autocorrelated based on the results of Moran’s I. Regression models addressing spatial aspects, see e.g. [12], could be used for the analysis in the future. Although stepwise regression is an efficient method of selecting predictive variables from a large dataset, it remains a controversial choice as stepwise regression does not always keep truly useful predictive variables and thus potentially harm the accuracy of the model [54]. The determinants identified by the regressions are not necessarily drivers of heat pump diffusion in Switzerland, either. Hence, a more sophisticated variable selection method, ideally driven by theory, would be more suitable to have a better comprehension of the situation of heat pump diffusion in Switzerland. Second, data of some determinants are unavailable at the municipal level like most determinants. Although these determinants can still have their effects measured by the regression models, the results might not be as reliable as data with a higher spatial resolution. Therefore, input data need to be rendered available at the municipal level to improve the precision of the regression models, and more data need to be gathered to achieve this goal. Third, our analyses have only been done on the year 2021. To have a spatiotemporal view of the results, additional analyses on several past years are required. More analyses could also be done to understand what makes German-speaking cantons generally outshine French-speaking cantons in respect of heat pump diffusion and especially what the role of cantonal policies is. Finally, the Swiss Federal Register of Buildings and Dwellings provided the best available spatial data on Swiss residential buildings, but there may be some biases in the data, e.g. some cantons might have been updating the data longer than others. For now, we attributed the cantonal hot and cold spots to the role of cantonal policies, but there may well be an effect of the quality of cantonal data. Also, the two indicators used in our study count merely the number of buildings heated by heat pumps instead of number of heat pump installations directly. Although our indicators are the best acquirable data at the moment and serve as a good proxy, it would be better to include number of heat pump installations in the future to acquire more accurate results. The analyses can even be oriented to explore the spatial diffusion patterns of heat pumps of different heat sources.

4.6 Conclusions

This study investigates residential heat pump diffusion in 2'148 Swiss municipalities in 2021, with a dataset covering approximatively 95.8% of Swiss residential buildings. Both stepwise regressions and spatial analysis confirm that heat pump diffusion is spatially heterogeneous throughout Switzerland, measured by the number of buildings heated by heat pumps per 1'000 buildings and per 1'000 inhabitants. The share of agricultural area and the share of detached houses of a municipality are found to have the largest positive influence on heat pump diffusion in Switzerland, indicating that rural municipalities are a main driver of heat pump diffusion. Economic factors, such as higher income or lower electricity price, do not appear to be influential, with the exception that the cantons with a higher unemployment rate tend to have a lower heat pump diffusion level. Cantonal heat pump policies possibly have a strong impact on heat pump diffusion, as significant differences in heat pump diffusion are identified in some cantons. Regional spatial spillovers are found to influence heat pump diffusion as well, either at inter-cantonal or cantonal level. Overall, our study contributes to the existing literature by confirming with the example of residential heat pumps that the diffusion of granular renewable energy technologies is spatially heterogeneous and subject to many sociodemographic, technoeconomic and housing characteristics. Future heat pump policies could integrate spatial heterogeneity and regional specificities to further promote heat pumps and accelerate energy transition process. The methodology of this study can also be applied to similar cases.

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5 Appendices

5.1 Appendices of chapter 2

5.1.1 Appendix A

5.1.1.1 Flow chart of methods and assumptions

Our main article visualizes the creation of our probabilistic projections in a four-step process. To ensure transparency, Table 5-1a-e lists the input data, a short description of tasks performed, the underlying assumptions, and the output that is created. We illustrate the steps using our case study on solar PV, heat pumps, and Battery Electric Vehicles (BEV) in Swiss municipalities.

Table 5-1a. Step 0 of the methods flow for creating probabilistic projections of technology diffusion.

0. Data preparation		
Input	Description	Output
Raw data: - Historical time series of a diffusion of a technology - Limits of diffusion (e.g., technical potentials) - List of municipalities - Size of population for each municipality	Task: Clean, filter and merge raw data. Assumptions on historical data: - Solar PV: total installed capacity in the installation year - Heat pumps: approximated by the number of registered buildings with a heat pump and an installation year based on the combination of the construction year of the building and the year when the heating system data was updated - Battery Electric Vehicles (BEV): number of registered BEV in the municipality of the owner's address Assumptions on potentials: - Solar PV: total installable capacity on roofs and facades (technical potential), - Heat pumps: total number of registered buildings in 2021 - BEV: total number of registered civil passenger cars in 2021	Historical time series of a diffusion of a technology: - Solar PV (years 2000-2021): installed capacity (absolute, per 100 inhabitants, and per technical potential in kW) - Heat pumps (2001-2021): number of buildings with a heat pump (absolute, per 100 inhabitants, and per total number of registered buildings in 2021) - BEV (2015-2021): number of registered civil passenger cars (absolute, per 100 inhabitants, and per total number of registered civil passenger cars in 2021)

Table 5-1b. Step 1 of the methods to create probabilistic projections of technology diffusion.

1. Deterministic projections for each municipality and 12 S-curve models		
Input	Description	Output
Historical time series of a diffusion of a technology Six uniform S-curve models: - Bass - Bertalanffy - Gompertz - Logistic - Four-parameter Richards (Richards-4p) - Five-parameter Richards (Richards-5p) Six Bi-S-curve models: - Bi-Bass - Bi-Bertalanffy - Bi-Gompertz - Bi-Logistic - Bi-Richards-4p - Bi-Richards-5p	Task: 1. Exclude historical time series with missing, static, quasi-static and highly fluctuating values. 2. Fit all S-curve models to the historical time series of a diffusion of a technology for a given range of years using non-linear least squares optimization: - Solar PV: 2000-2021 - Heat pumps: 2001-2021 - BEV: 2015-2021 A differential evolution method determines the initial guess of model parameters used in the least squares optimization. Assumptions: - The diffusion of a technology follows the shape of an S-curve. - The range of possible parameter values is bounded.	Deterministic projections for each technology, each municipality and twelve S-curve models

Table 5-1c. Step 2 of the methods to create probabilistic projections of technology diffusion.

2. Probabilistic projections for each municipality and each S-curve model		
Input	Description	Output
Historical time series of a diffusion of a technology Deterministic projections for each technology, each municipality and twelve S-curve models	Task: 1. Define similar municipalities: Normalize using the value of the last year used for curve fitting and compare the historical time series by calculating the Euclidean distance. 2. Create probabilistic projections: Combine all deterministic projections of similar municipalities for each S-curve model and calculate the quantiles of the resulting distribution. Assumptions: - Municipalities are considered similar if the mean Euclidean distance between their normalized historical time series is lower than the 30% quantile of the mean Euclidean distance to all municipalities - Probabilistic density intervals derive from the variation of projections of different S-curve models and similar municipalities	Probabilistic projections for each technology, each municipality and twelve S-curve models

Table 5-1d. Step 3 of the methods to create probabilistic projections of technology diffusion.

<table>
<tr><th colspan="3">3. Performance evaluation of each S-curve model using hindcasting</th></tr>
<tr><th>Input</th><th>Description</th><th>Output</th></tr>
<tr>
<td><u>Probabilistic projections for each technology, each municipality and twelve S-curve models</u>

<u>Metrics of model performance:</u>
- Saturation below real value of 2021
- Mean Absolute Percentage Error (MAPE)
- Sharpness
- Calibration
- Weighted Interval Score (WIS)</td>
<td><u>Task:</u>
1. Evaluate the performance of each probabilistic projection using iterative hindcasting: Repeat steps 1 and 2, vary the years used for curve fitting and evaluation in each iteration, and calculate metrics of model performance relative to each observation for
- One- to ten-year-ahead projections (solar PV and heat pumps)
- One- to four-year-ahead projections (BEV)
2. Assign weights to each probabilistic projection of an S-curve model and municipality using the inverse of the mean squared weighted interval score</td>
<td><u>Scores of performance metrics of deterministic and probabilistic projections for each S-curve model, municipality, and technology</u>

<u>Weights for each S-curve model of each municipality and technology</u></td>
</tr>
</table>

Table 5-1e. Step 4 of the methods to create probabilistic projections of technology diffusion.

4. Probabilistic projections for each municipality using weighted models		
Input	Description	Output
<u>Probabilistic projections for each technology, each municipality and twelve S-curve models</u> <u>Weights for each S-curve model of each municipality and technology</u>	<u>Task:</u> 1. Create probabilistic projections by combining the probabilistic projections the S-curve models according to the calculated weights and taking the quantiles of the resulting distribution. 2. Create probabilistic projections for municipalities that have been excluded in step 1 using average weights and growth rates. <u>Assumption:</u> - The best performing models of the past will also be the best in the future. - The diffusion of technologies in excluded municipalities will follow the shape of S-curves from the first projected year onwards.	<u>Probabilistic projections for each municipality and technology based on weighted models</u>

5.1.1.2 Sensitivity analysis of the influence of the quantile of the mean Euclidean distance on the probabilistic projections

To justify the use of the 30% quantile of the mean Euclidean distance as a cutoff to define whether two municipalities are similar, we perform a sensitivity analysis of the quantile value and discuss the tradeoffs coming with the choice of a value. We perform the sensitivity analysis on the case of solar PV capacity since the technology both has the longest historical time series available for hindcasting and results in largest differences in performances of the models compared to the other technologies. We find that the performance of all models in terms of MAPE and WIS consistently increases or decreases with the increase or decrease of the quantile cutoff value and by this, the number of curves based on which the probabilistic density intervals are created (Figure 5-1 and Figure 5-2). Here, the comparatively low performing models show highest sensitivity to the used quantile, i.e., the magnitudes of increase or decrease in the performance are highest. Consequently, the difference in weights and scores between the models increases with the use of a lower quantile and decreases with the use of a higher quantile.

Although the results of the sensitivity analysis point towards using a higher quantile, there are a couple of tradeoffs that come with a higher cutoff: (i) computational costs increase, especially in terms of computation time and required memory storage, (ii) the degree of similarity of additional historical time series treated as similar in the creation of probabilistic projections lowers, and by this, (iii) the shape of the probabilistic density intervals of all municipalities become more similar to each other and thus counteract the goal of creating individual projections for each municipality. The value of the quantile also should not be too low since a low quantile can result in a number of curves that might not be too low to create a meaningful probabilistic density interval that can compensate outliers in the set of curves. As we calculate 99 quantiles (0.01-0.99) that make up the probabilistic density interval (0.01-0.99), we target to have a couple of hundred curves based on which we create the probabilistic density intervals for each municipality. Taking all tradeoffs into consideration, we use the 30% quantile as a compromise for the computation of the results of our case study.

model	MAPE	sharpness / WIS	calibration / WIS	WIS	weight	MAPE	sharpness / WIS	calibration / WIS	WIS	weight	MAPE	sharpness / WIS	calibration / WIS	WIS	weight	MAPE	sharpness / WIS	calibration / WIS	WIS	weight	MAPE	sharpness / WIS	calibration / WIS	WIS	weight
Bass	1.04	0.23	0.77	3.57	4.83	0.97	0.26	0.74	3.31	5.16	0.91	0.28	0.72	3.12	5.47	0.80	0.36	0.64	2.58	5.87	0.65	0.44	0.56	2.17	6.46
Bertalanffy	0.37	0.06	0.94	1.52	18.64	0.37	0.06	0.94	1.51	17.99	0.37	0.07	0.93	1.49	17.37	0.37	0.07	0.93	1.48	16.62	0.36	0.07	0.93	1.46	15.58
Gompertz	0.77	0.25	0.75	2.57	7.90	0.71	0.28	0.72	2.33	8.36	0.65	0.32	0.68	2.08	8.72	0.56	0.38	0.62	1.79	9.29	0.46	0.42	0.58	1.57	9.85
Logistic	1.02	0.23	0.77	3.55	4.97	0.96	0.26	0.74	3.28	5.30	0.89	0.27	0.73	3.10	5.64	0.78	0.35	0.65	2.57	6.07	0.63	0.44	0.56	2.12	6.76
Richards-4p	0.58	0.11	0.89	2.14	8.67	0.57	0.12	0.88	2.09	8.61	0.57	0.13	0.87	2.04	8.56	0.56	0.14	0.86	2.00	8.52	0.55	0.15	0.85	1.95	8.48
Richards-5p	0.57	0.12	0.88	2.08	8.78	0.56	0.13	0.87	2.03	8.76	0.55	0.14	0.86	1.98	8.73	0.55	0.15	0.85	1.93	8.69	0.54	0.16	0.84	1.88	8.67
Bi-Bass	1.03	0.29	0.71	3.54	4.31	0.97	0.32	0.68	3.31	4.41	0.90	0.36	0.64	3.08	4.52	0.83	0.44	0.56	2.69	4.65	0.74	0.52	0.48	2.39	4.78
Bi-Bertalanffy	0.37	0.06	0.94	1.52	18.51	0.37	0.06	0.94	1.51	17.87	0.37	0.06	0.94	1.49	17.26	0.37	0.07	0.93	1.48	16.50	0.36	0.07	0.93	1.47	15.46
Bi-Gompertz	0.73	0.64	0.36	3.28	5.13	0.68	0.66	0.34	3.16	5.22	0.64	0.69	0.31	3.03	5.29	0.56	0.73	0.27	2.84	5.31	0.47	0.77	0.23	2.67	5.23
Bi-Logistic	1.09	0.67	0.33	7.73	1.41	1.02	0.67	0.33	6.90	1.49	0.95	0.67	0.33	6.30	1.56	0.86	0.71	0.29	5.46	1.69	0.71	0.78	0.22	4.86	1.82
Bi-Richards-4p	0.59	0.15	0.85	2.09	8.27	0.58	0.16	0.84	2.03	8.25	0.57	0.17	0.83	1.98	8.22	0.56	0.18	0.82	1.93	8.18	0.55	0.20	0.80	1.87	8.22
Bi-Richards-5p	0.59	0.14	0.86	2.14	8.47	0.58	0.15	0.85	2.08	8.47	0.58	0.16	0.84	2.03	8.52	0.57	0.17	0.83	1.97	8.56	0.55	0.19	0.81	1.91	8.61
	quantile: 20%					quantile: 25%					quantile: 30%					quantile: 35%					quantile: 40%				

Figure 5-1. Heat map with weights and scores of model performance from hindcasting for solar PV capacity for different quantiles used as a similarity criterion in the creation of probabilistic projections. The values for the 30% quantile are the same as in the heat map of the main article. All shown values are means over all municipalities and hindcasting iterations with one- to ten-year ahead projections. The Mean Absolute Percentage Error (MAPE) of a probabilistic projection quantifies the error between the median value of the projection and the real value. For each column, colors rank each score from highest (red) to lowest (blue) and vice versa for the weight. WIS: Weighted Interval Score that approximates the Continuous Ranked Probability Score.

model	MAPE	sharpness / WIS	calibration / WIS	WIS	weight	MAPE	sharpness / WIS	calibration / WIS	WIS	weight		MAPE	sharpness / WIS	calibration / WIS	WIS	weight	MAPE	sharpness / WIS	calibration / WIS	WIS	weight
Bass	0.14	-0.17	0.07	0.15	-0.12	0.07	-0.08	0.03	0.06	-0.06		-0.12	0.28	-0.11	-0.17	0.07	-0.29	0.59	-0.23	-0.30	0.18
Bertalanffy	0.01	-0.09	0.01	0.02	0.07	0.00	-0.04	0.00	0.01	0.04		-0.01	0.05	0.00	-0.01	-0.04	-0.01	0.09	-0.01	-0.02	-0.10
Gompertz	0.19	-0.23	0.11	0.23	-0.09	0.10	-0.12	0.06	0.12	-0.04		-0.14	0.20	-0.09	-0.14	0.06	-0.29	0.33	-0.15	-0.25	0.13
Logistic	0.14	-0.16	0.06	0.15	-0.12	0.07	-0.07	0.02	0.06	-0.06		-0.12	0.27	-0.10	-0.17	0.08	-0.30	0.59	-0.22	-0.31	0.20
Richards-4p	0.02	-0.14	0.02	0.05	0.01	0.01	-0.07	0.01	0.02	0.01		-0.01	0.07	-0.01	-0.02	-0.01	-0.02	0.15	-0.02	-0.05	-0.01
Richards-5p	0.02	-0.15	0.02	0.05	0.01	0.01	-0.08	0.01	0.02	0.00		-0.01	0.08	-0.01	-0.02	-0.01	-0.03	0.16	-0.03	-0.05	-0.01
Bi-Bass	0.14	-0.20	0.11	0.15	-0.05	0.07	-0.10	0.06	0.07	-0.02		-0.08	0.21	-0.12	-0.13	0.03	-0.18	0.44	-0.25	-0.22	0.06
Bi-Bertalanffy	0.01	-0.09	0.01	0.02	0.07	0.00	-0.04	0.00	0.01	0.04		-0.01	0.05	0.00	-0.01	-0.04	-0.01	0.09	-0.01	-0.02	-0.10
Bi-Gompertz	0.15	-0.07	0.15	0.08	-0.03	0.08	-0.04	0.08	0.04	-0.01		-0.12	0.06	-0.14	-0.06	0.00	-0.26	0.11	-0.25	-0.12	-0.01
Bi-Logistic	0.14	0.00	0.01	0.23	-0.10	0.07	0.00	0.00	0.09	-0.05		-0.10	0.07	-0.14	-0.13	0.08	-0.25	0.16	-0.33	-0.23	0.17
Bi-Richards-4p	0.03	-0.15	0.03	0.05	0.01	0.01	-0.07	0.01	0.02	0.00		-0.01	0.08	-0.02	-0.03	-0.01	-0.04	0.16	-0.03	-0.06	0.00
Bi-Richards-5p	0.03	-0.15	0.03	0.06	-0.01	0.01	-0.08	0.01	0.03	-0.01		-0.02	0.07	-0.01	-0.03	0.00	-0.04	0.16	-0.03	-0.06	0.01
	quantile: 20%					quantile: 25%					30%	quantile: 35%					quantile: 40%				

Figure 5-2. Heat map with percentage differences of weights and scores of model performance for solar PV capacity for different quantiles used as a similarity criterion in the creation of probabilistic projections compared to weights and scores of the 30% quantile. Figure 5-1 shows the absolute weights and scores. Colors rank each value from zero (white) to highest and lowest difference (red). WIS: Weighted Interval Score that approximates the Continuous Ranked Probability Score.

5.1.1.3 Data on heat pumps

The Swiss Federal Register of Buildings and Dwellings (1) registers for each building the heating technology installed as a primary or secondary heating system for space heating or warm water. However, the register does not specify the installed capacities, years of installation, nor is it clear how complete the register is in terms of total number of registered buildings and up-to-date information on heating systems. Nevertheless, it is the most complete dataset of buildings in Switzerland that, for instance, the Federal Statistical Office (2–4) or Energy Reporter (5) use for aggregated statistics. We take the following steps to derive a historical time series of the diffusion of heat pumps in Switzerland:

1. We filter for each municipality the register for existing buildings that have a heat pump registered as primary or secondary heating system for space heating or warm water. It is indistinguishable whether a building uses a heating system for multiple purposes or whether there exist separate heat pumps for the different heating purposes.
2. We assume that the installation year of a heat pump in a building is the same as the construction year of the building. If the construction year is missing in the register, we use the year in which the information of the primary space heating system is updated in the register. Note that the date of information update is not necessarily the same as the installation year. If the date of information update of the primary space heating system is missing, we use the earliest year of the three dates of information update of secondary space heating system, primary warm water heating system, and secondary warm water heating system. We argue that the error that derives from our assumption to use the construction year of a building is limited since the average lifetime of a heating system is 20 years (6) and the maximum number of years we use for curve fitting is 21. Therefore, we expect the real installation year to lay within the time range that we use for curve fitting.
3. Since the first two steps can result in multiple remaining entries of the same building, e.g., if a heat pump is registered as a heating system for space heating and warm water, we remove all duplicates to avoid double counting. For practical reasons, we count buildings only more than once if the installation years that we assume are different for primary or secondary space heating or warm water supply. This is the case for less than 0.7% of all registered buildings with heat pumps.

When we compare the sum of our derived historical time series with other datasets, we see comparable diffusion of heat pumps. For instance, the model for the electrical heat pump statistics (7, 8) estimates a similar level of diffusion in Switzerland, although its growth rate is higher. As both their model and our derivation use assumptions, it remains uncertain how the real diffusion evolves over time. However, we assume that the errors spread equally across the municipalities and therefore have only little effect on the comparison of different municipalities.

5.1.1.4 Data on local capacity factors for solar PV and technical potential

We use local capacity factors to estimate the average annual power generation of installed solar PV capacities in each municipality of Switzerland and to convert generation potentials into capacities. First, we download the capacity factors for solar PV from Renewables.ninja (9, 10) for all coordinates of the geographical centers of the 2’148 Swiss municipalities (11). We take the “MERRA2” dataset and extract the capacity factors for every hour of the latest available year, i.e., 2020. For every municipality, we assume a system loss of 0.1, no tracking, a tilt of 35° and an azimuth of 180° to represent the average orientation angles of solar PV panels in a municipality. Second, we take the annual solar power generation potentials of each municipality estimated in a scenario that considers solar PV on roofs and facades (12). Finally, we convert the generation potentials into capacities using the local capacity factors and an average electricity output ratio of 950 kWh/kW for Switzerland that represents a conservative estimate based on electricity outputs of solar PV panels observed per year (13, 14). We calculate electricity output ratios for each municipality by weighting the Swiss average electricity output with the annual mean of a local capacity factor over the annual mean of the average capacity factor of all municipalities.

5.1.1.5 Projections for municipalities with missing, quasi-static or highly fluctuating historical time series of diffusion

The S-curve models we use in our study assume growth in technology diffusion that the historical time series data might not represent if the time series is static, quasi-static or highly fluctuating. Therefore, we exclude municipalities prior to applying our four-step methods if their historical time series meet at least one of the following criteria:

- All values are zero;
- One of the last three values used for curve fitting is zero;
- The last five (for BEV: three) values used for curve fitting are the same;
- The historical time series drops by at least 50% in value from one year to another.

One example of outliers is the municipality of Dielsdorf where the number of registered BEV more than doubles from 2016 to 2018 and eventually drops to almost half of the vale of 2015 in 2021. We assume that this atypical behavior is due to registrations of the car manufacturer Bayerische Motoren Werke that has its Swiss headquarters in Dielsdorf (15) and the time series does not represent the true diffusion of BEV in this municipality.

To create a probabilistic projection of technology growth for the excluded municipalities, we assume that their technology diffusion follows the average growth of all Swiss municipalities from the first projected year, i.e., 2022, onwards. First, we take for each S-curve model the quantiles of the combined normed probabilistic projections of all non-excluded Swiss municipalities. Second, we calculate the average weights of the S-curve models of all non-excluded Swiss municipalities (see, e.g., Figure 5-3). Finally, we multiply the quantiles with the last value of the historical time series of an excluded municipality to create a probabilistic projection and combine the projections using the average model weights. If the last value in the historical time series is zero, we multiply with a dummy variable that we subtract again from the projected values, to shift the starting point of the diffusion back to zero. We define the dummy variable as the median of the initial installation capacity of all municipalities. The initial installation capacity is the total installed capacity of a municipality in the first year in which the capacity is larger than zero.

5.1.1.6 Determination of S-curve parameters

To determine the values of S-curve parameters, as shown in Section 2.5, so that the curve fits the historical time series of a diffusion of a technology best, we use a non-linear least squares optimization with initial guess and bounds for the parameters. Since the initial guess of model parameters influences the determination of optimal parameters notably, we employ a differential evolution method (16, 17) that uses random inputs to find the optimal set of values for the initial guess. For each S-curve model, we feed the same parameter bounds into the differential evolution that we also use for the least squares optimization and take the following assumptions:

- The level of saturation C lays between the last value in the historical time series that we use for curve fitting and the potential limit and C has the same unit as the variable that is described by the S-curve, e.g., kW for the variable of solar PV capacity.
- The position of the inflection point t_0 given in years lays within this century, i.e., between the years 2000 and 2100, for logistic, Gompertz, and Bass models, and between 1900 and 2100 for Bertalanffy and the two versions of the generalized Richards model.
- The unitless degree of a function d is limited to a maximum of ten to reduce computational complexity.
- The vertical shift z lays between zero and the first value in the historical time series that was used for curve fitting and has the same unit as C.
- The unitless curve parameters b, k, p, q lay within zero and one to reduce computational complexity.

For the Bi-S-curve models, we use an additional constraint so that the level of saturation C of the second growth phase must be higher or equal to the saturation level of the first growth phase.

5.1.2 Appendix B

5.1.2.1 Heat maps with wights and scores of model performance from hindcasting

model	share of curves saturating below real value of 2021	MAPE (point projection)	MAPE (probabilistic proj.)	sharpness / WIS	calibration / WIS	WIS	weight	share of curves saturating below real value of 2021	MAPE (point projection)	MAPE (probabilistic proj.)	sharpness / WIS	calibration / WIS	WIS	weight	share of curves saturating below real value of 2021	MAPE (point projection)	MAPE (probabilistic proj.)	sharpness / WIS	calibration / WIS	WIS	weight
Bass	0.63	3.28	0.84	0.28	0.71	2.88	5.36	0.58	0.22	0.12	0.26	0.73	0.34	10.57	0.31	0.80	0.32	0.44	0.55	1.12	13.85
Bertalanffy	0.05	0.44	0.36	0.07	0.93	1.47	17.45	0.34	0.16	0.09	0.33	0.66	0.29	15.69	0.28	0.52	0.31	0.25	0.74	1.08	22.24
Gompertz	0.55	1.81	0.60	0.32	0.68	1.95	8.40	0.49	0.18	0.10	0.32	0.67	0.31	12.72	0.31	3.58	0.33	0.66	0.32	2.13	5.83
Logistic	0.64	3.39	0.82	0.28	0.71	2.85	5.45	0.59	0.23	0.12	0.27	0.72	0.34	10.53	0.33	0.88	0.36	0.42	0.57	1.20	12.35
Richards-4p	0.10	0.92	0.56	0.13	0.87	2.01	8.19	0.35	0.18	0.09	0.35	0.64	0.29	15.42	0.29	1.01	0.31	1.00	0.00	> 10	10.42
Richards-5p	0.12	0.92	0.54	0.14	0.86	1.95	8.34	0.35	0.18	0.09	0.35	0.65	0.29	15.32	0.27	0.98	0.33	1.00	0.00	> 10	11.10
Bi-Bass	0.50	3.11	0.85	0.37	0.62	2.89	4.29	0.61	0.26	0.11	0.44	0.55	0.34	8.87	0.27	1.49	0.38	0.73	0.26	1.62	7.43
Bi-Bertalanffy	0.05	0.44	0.36	0.07	0.92	1.49	17.07	0.31	0.18	0.09	1.00	0.00	> 10	0.01	0.18	0.57	0.30	1.00	0.00	> 10	0.24
Bi-Gompertz	0.36	4.09	0.58	0.67	0.32	2.75	5.34	0.35	0.59	0.09	0.62	0.37	0.39	8.02	0.21	4.09	0.33	0.84	0.15	2.93	2.81
Bi-Logistic	0.44	3.95	0.88	0.36	0.62	3.01	4.49	0.45	0.70	0.10	1.00	0.00	> 10	2.15	0.27	0.87	0.37	0.51	0.48	1.22	11.01
Bi-Richards-4p	0.13	1.07	0.56	0.17	0.83	1.95	7.72	0.35	0.23	0.09	1.00	0.00	> 10	0.68	0.12	0.89	0.30	1.00	0.00	> 10	1.48
Bi-Richards-5p	0.07	1.13	0.57	0.17	0.82	1.98	7.85	0.37	0.23	0.09	1.00	0.00	> 10	0.00	0.15	0.98	0.30	1.00	0.00	> 10	1.26
	Solar PV capacity per 100 inhabitants							Buildings with a heat pump per 100 inhabitants							Registered BEV per 100 inhabitants						

Figure 5-3. Heat map with weights and scores of model performance from hindcasting for solar PV capacity, heat pumps and BEV per 100 inhabitants. For each column, colors rank each score from highest (red) to lowest (blue) and vice versa for the weight. The shown values are means over all municipalities and hindcasting iterations with one- to ten-year ahead projections for solar PV and heat pumps, and one- to four-year ahead projections for Battery Electric Vehicles (BEV). For temporal evolutions, see Figures 5-8 – 5-12. The Mean Absolute Percentage Error (MAPE) of a probabilistic projection quantifies the error between the median value of the projection and the real value. To enhance comparability as some Bi-S-curves have scores that are multiple orders higher than 10, the highest 2% of MAPE scores, sharpness, calibration and Weighted Interval Scores (WIS) are removed for all models before taking the mean. Models that still have mean scores above 10 are indicated.

model	share of curves saturating below real value of 2021	MAPE (point projection)	MAPE (probabilistic proj.)	sharpness / WIS	calibration / WIS	WIS	weight	share of curves saturating below real value of 2021	MAPE (point projection)	MAPE (probabilistic proj.)	sharpness / WIS	calibration / WIS	WIS	weight	share of curves saturating below real value of 2021	MAPE (point projection)	MAPE (probabilistic proj.)	sharpness / WIS	calibration / WIS	WIS	weight
Bass	0.62	3.43	0.89	0.31	0.67	3.00	5.21	0.50	0.23	0.12	0.29	0.70	0.34	9.43	0.31	0.78	0.33	0.38	0.61	1.11	13.50
Bertalanffy	0.04	0.43	0.36	0.06	0.93	1.45	17.36	0.25	0.16	0.09	0.35	0.65	0.29	15.31	0.28	0.52	0.32	0.24	0.76	1.09	18.69
Gompertz	0.54	1.84	0.60	0.36	0.64	1.92	8.79	0.39	0.19	0.10	0.35	0.64	0.30	12.04	0.31	3.61	0.33	0.59	0.39	1.91	6.03
Logistic	0.63	3.48	0.88	0.31	0.68	2.99	5.20	0.52	0.24	0.12	0.29	0.70	0.34	9.41	0.33	0.88	0.33	0.37	0.62	1.15	12.52
Richards-4p	0.09	0.90	0.55	0.13	0.87	1.97	8.54	0.27	0.18	0.09	0.37	0.62	0.28	14.95	0.30	0.96	0.33	1.00	0.00	> 10	8.98
Richards-5p	0.11	0.89	0.53	0.14	0.86	1.91	8.68	0.27	0.18	0.09	0.36	0.63	0.29	14.82	0.26	1.02	0.33	0.38	0.61	1.24	11.00
Bi-Bass	0.49	3.31	0.89	1.00	0.00	> 10	3.78	0.54	0.28	0.12	0.44	0.55	0.35	8.18	0.27	1.50	0.34	0.72	0.27	1.52	7.44
Bi-Bertalanffy	0.04	0.43	0.36	1.00	0.00	> 10	16.73	0.23	0.18	0.09	1.00	0.00	> 10	1.47	0.18	0.56	0.31	1.00	0.00	> 10	1.34
Bi-Gompertz	0.36	4.32	0.58	0.72	0.27	3.03	4.82	0.28	0.57	0.09	0.62	0.37	0.37	8.16	0.21	4.26	0.32	0.80	0.19	2.49	3.57
Bi-Logistic	0.44	4.04	0.94	0.39	0.59	3.18	4.27	0.39	0.75	0.10	1.00	0.00	> 10	4.02	0.28	0.87	0.33	1.00	0.00	> 10	11.02
Bi-Richards-4p	0.13	1.04	0.54	0.17	0.82	1.89	8.15	0.28	0.24	0.09	1.00	0.00	> 10	1.59	0.13	0.88	0.31	1.00	0.00	> 10	1.45
Bi-Richards-5p	0.08	1.12	0.55	0.18	0.81	1.90	8.37	0.30	0.24	0.09	1.00	0.00	> 10	0.60	0.15	0.95	0.31	1.00	0.00	> 10	4.41
	Solar PV capacity per technical potential							Buildings with a heat pump per registered buildings							Registered BEV per total civil passenger cars						

Figure 5-4. Heat map with weights and scores of model performance from hindcasting for solar PV capacity, heat pumps and BEV per potential. For each column, colors rank each score from highest (red) to lowest (blue) and vice versa for the weight. The shown values are means over all municipalities and hindcasting iterations with one- to ten-year ahead projections for solar PV and heat pumps, and one- to four-year ahead projections for Battery Electric Vehicles (BEV). For temporal evolutions, see Figures 5-8 – 5-12. The Mean Absolute Percentage Error (MAPE) of a probabilistic projection quantifies the error between the median value of the projection and the real value. To enhance comparability as some Bi-S-curves have scores that are multiple orders higher than 10, the highest 2% of MAPE scores, sharpness, calibration and Weighted Interval Scores (WIS) are removed for all models before taking the mean. Models that still have mean scores above 10 are indicated.

5.1.2.2 Distribution of weights for probabilistic projections of solar PV, heat pumps, and BEV

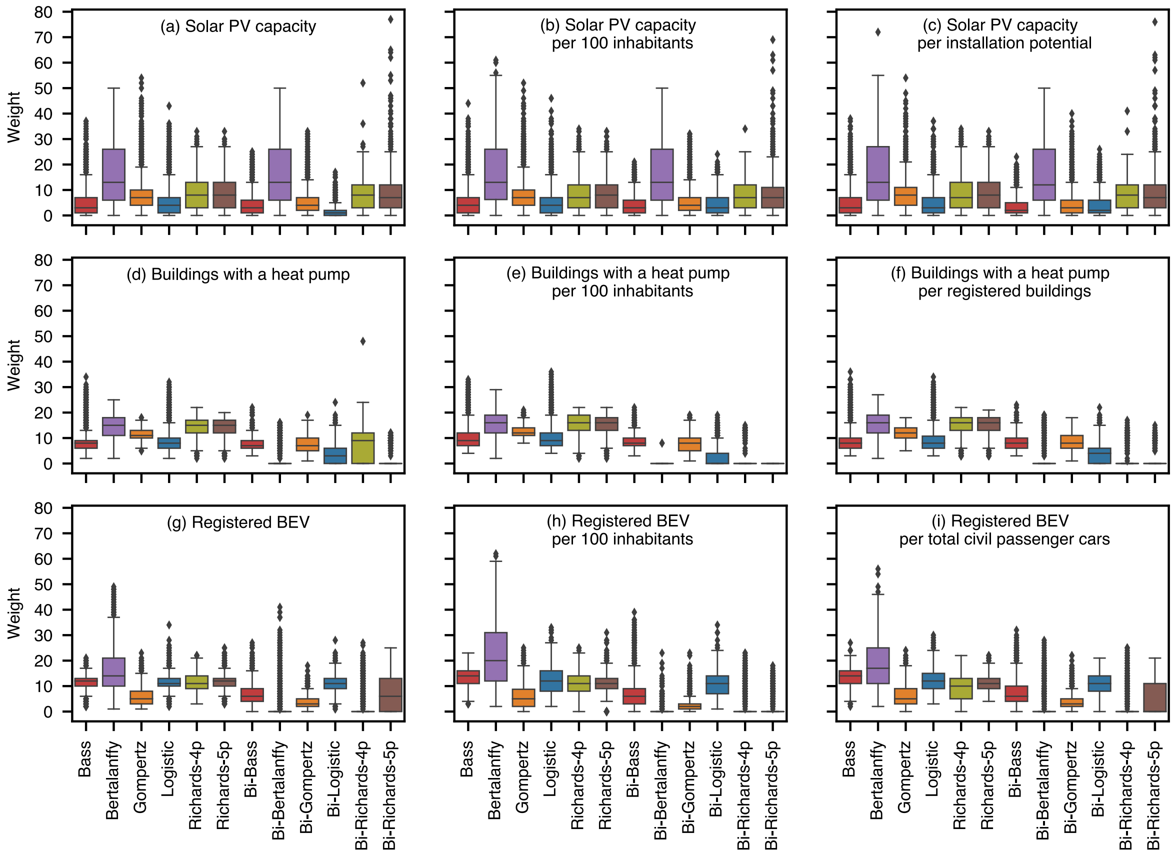

Figure 5-5. Box plots showing the distribution of weights for the probabilistic projections of solar PV capacities (a-c), heat pumps (d-f), and Battery Electric Vehicles (BEV) (g-i) across Swiss municipalities.

5.1.2.3 Diffusion of solar PV, heat pumps, and BEV across Switzerland in 2021

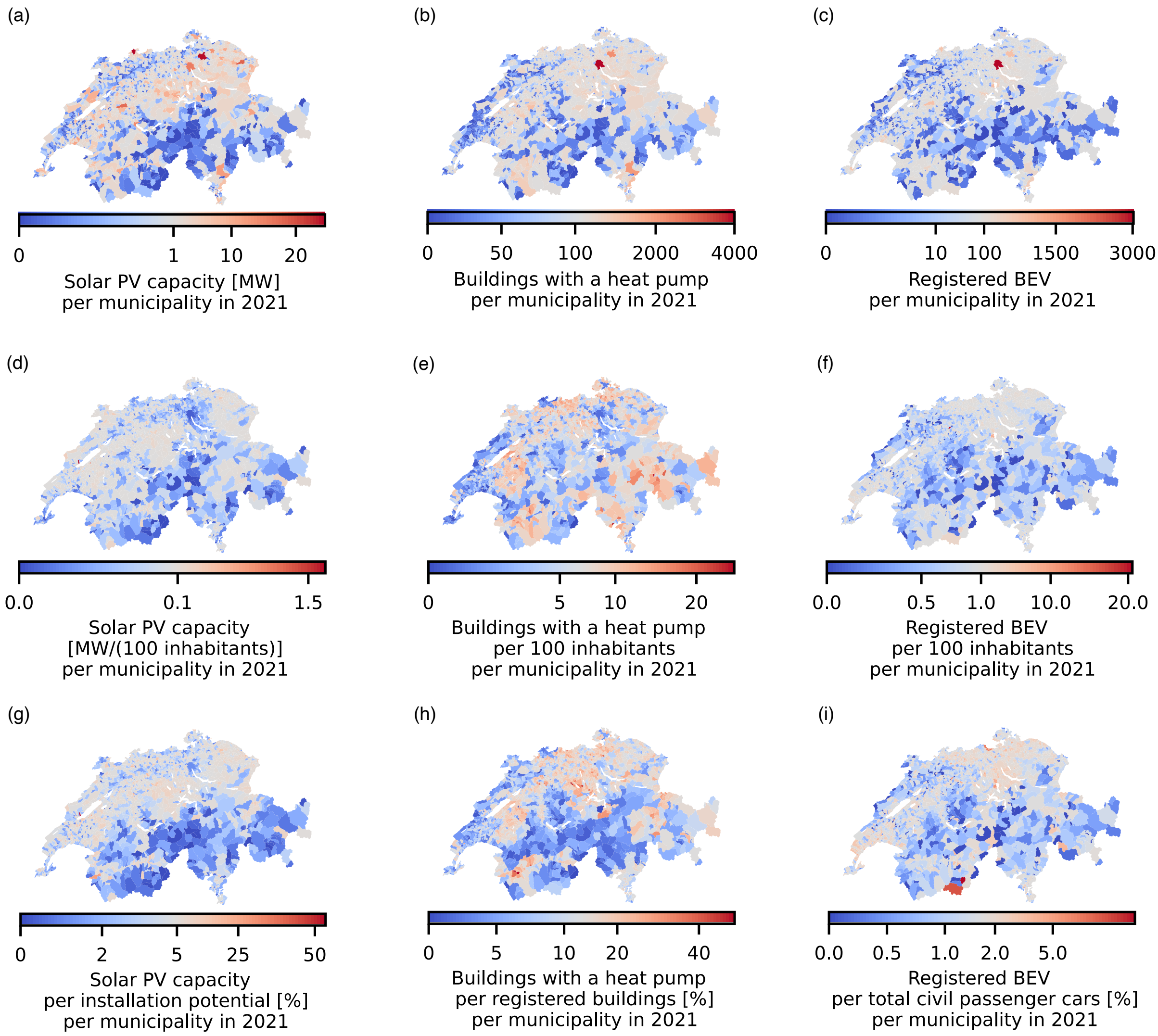

Figure 5-6. Distribution of solar PV capacities, heat pumps, and Battery Electric Vehicles (BEV) in total (a-c), per 100 inhabitants (d-f), and per potential (g-i) across Switzerland in 2021 with a quantile coloring scheme. Own visualization based on data from Swiss Federal Office of Energy and Federal Statistical Office (1, 13, 18).

5.1.2.4 Diffusion of solar PV, heat pumps, and BEV across Switzerland in 2050

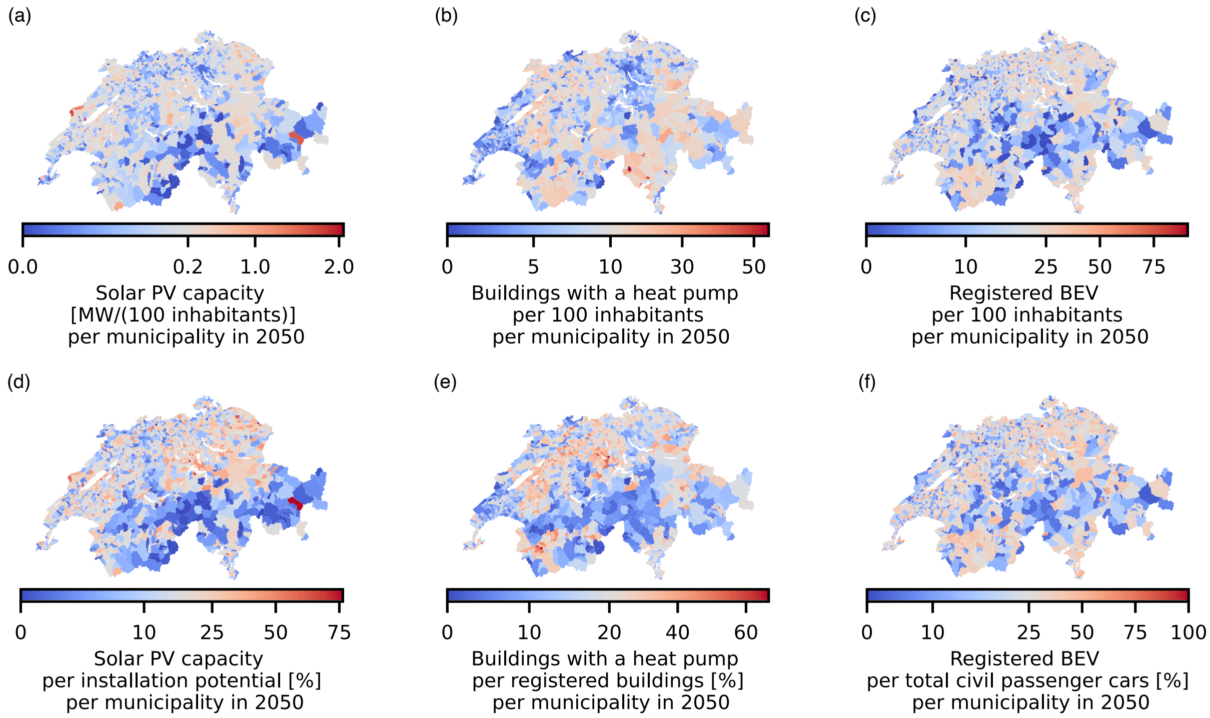

Figure 5-7. Distribution of solar PV capacities, heat pumps, and battery electric vehicles (BEV) per 100 inhabitants (a-c), and per potential (d-f) across Switzerland in 2050 according to the projected median values of the probabilistic projections of each municipality and a quantile coloring scheme.

5.1.2.5 Temporal evolution of the mean absolute percentage error for probabilistic and deterministic projections of solar PV, heat pumps, and BEV

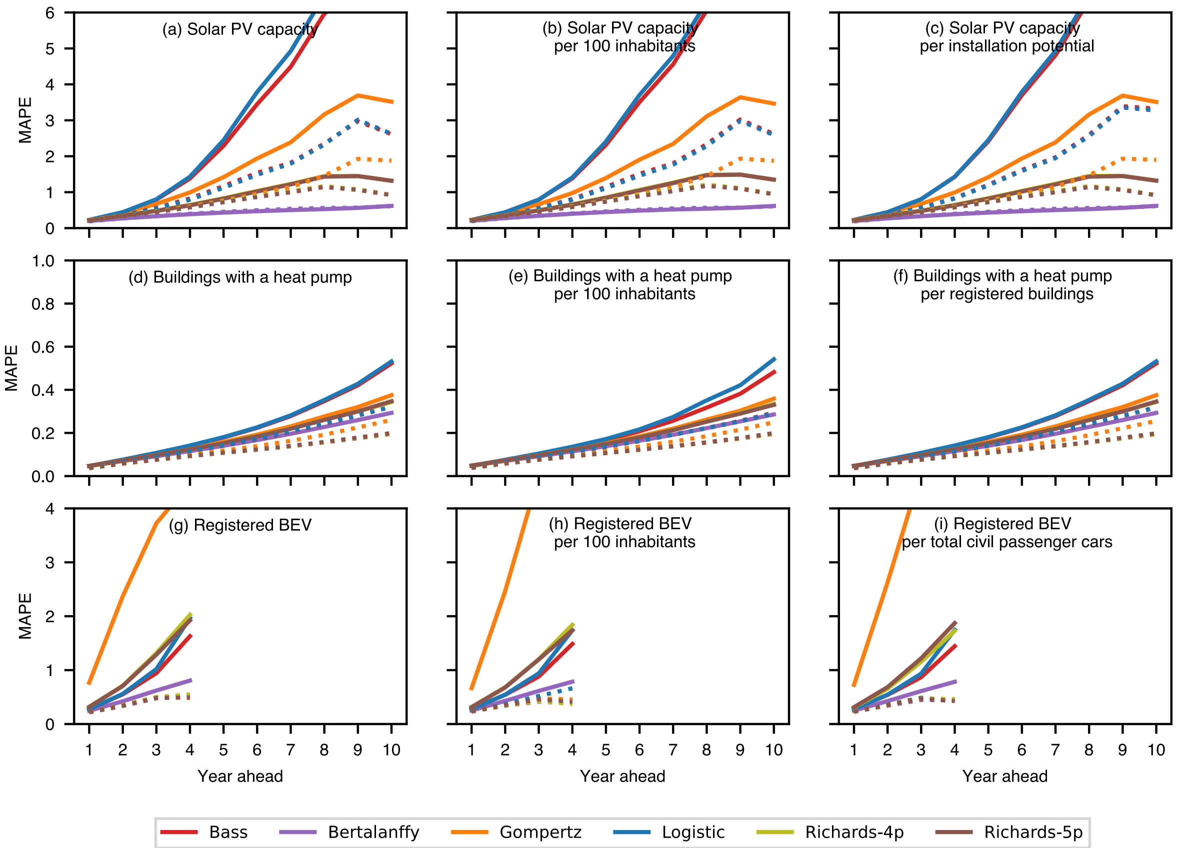

Figure 5-8. Temporal evolution of the Mean Absolute Percentage Error (MAPE) for the deterministic projections (solid lines) and probabilistic projections (dotted lines) of solar PV capacities (a-c), heat pumps (d-f), and Battery Electric Vehicles (BEV) (g-i) across Swiss municipalities and iterations of hindcasting. For visual clarity, this figure shows only uniform S-curve models whereas Figure 5-9 shows Bi-S-curve models. To enhance comparability as some Bi-S-curves have scores that are multiple orders higher than 10, the highest 2% of scores are removed for all models before taking the mean. Scores can lay outside the plot boundaries in certain years.

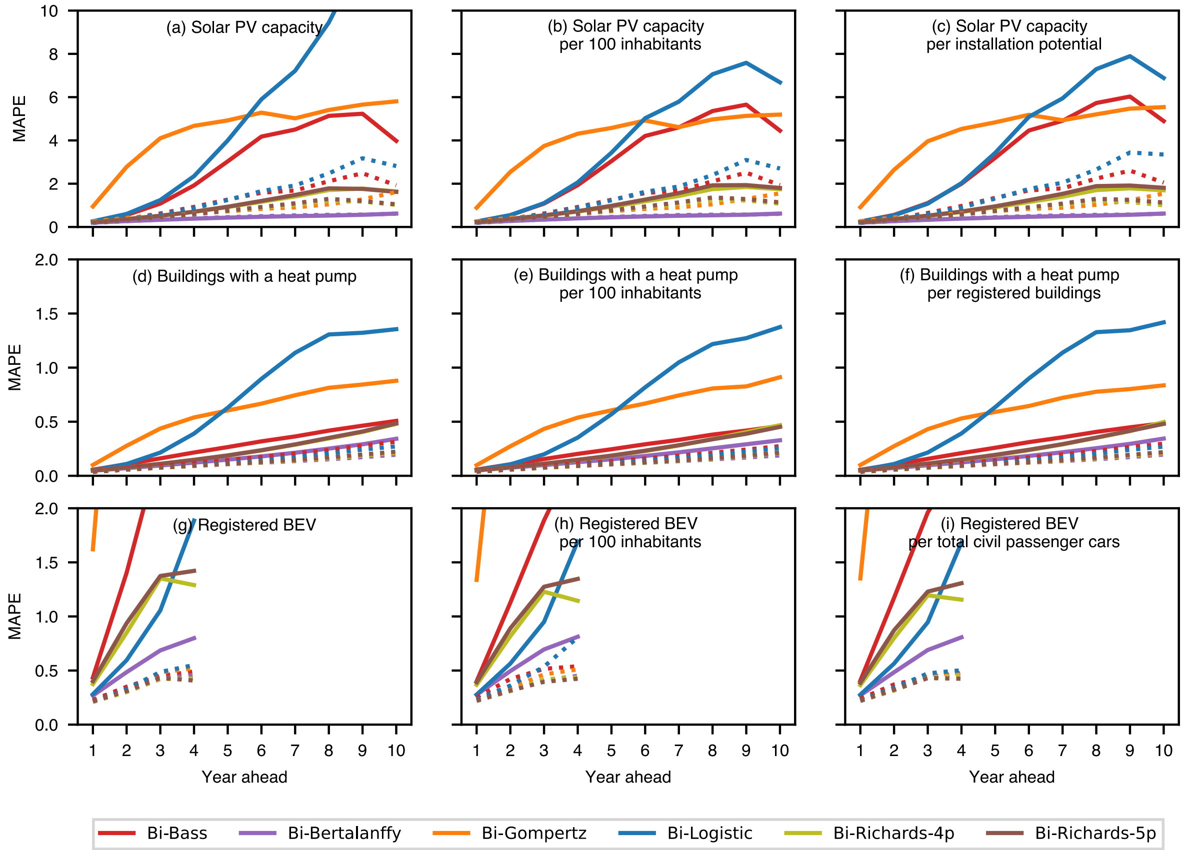

Figure 5-9. Temporal evolution of the Mean Absolute Percentage Error (MAPE) for the deterministic projections (solid lines) and probabilistic projections (dotted lines) of solar PV capacities (a-c), heat pumps (d-f), and Battery Electric Vehicles (BEV) (g-i) across Swiss municipalities and iterations of hindcasting. For visual clarity, this figure shows only Bi-S-curve models whereas Figure 5-8 shows uniform S-curve models. To enhance comparability as some Bi-S-curves have scores that are multiple orders higher than 10, the highest 2% of scores are removed for all models before taking the mean. Scores can lay outside the plot boundaries in certain years.

5.1.2.6 Temporal evolution of sharpness, calibration, and weighted interval score for probabilistic and deterministic projections of solar PV, heat pumps, and BEV

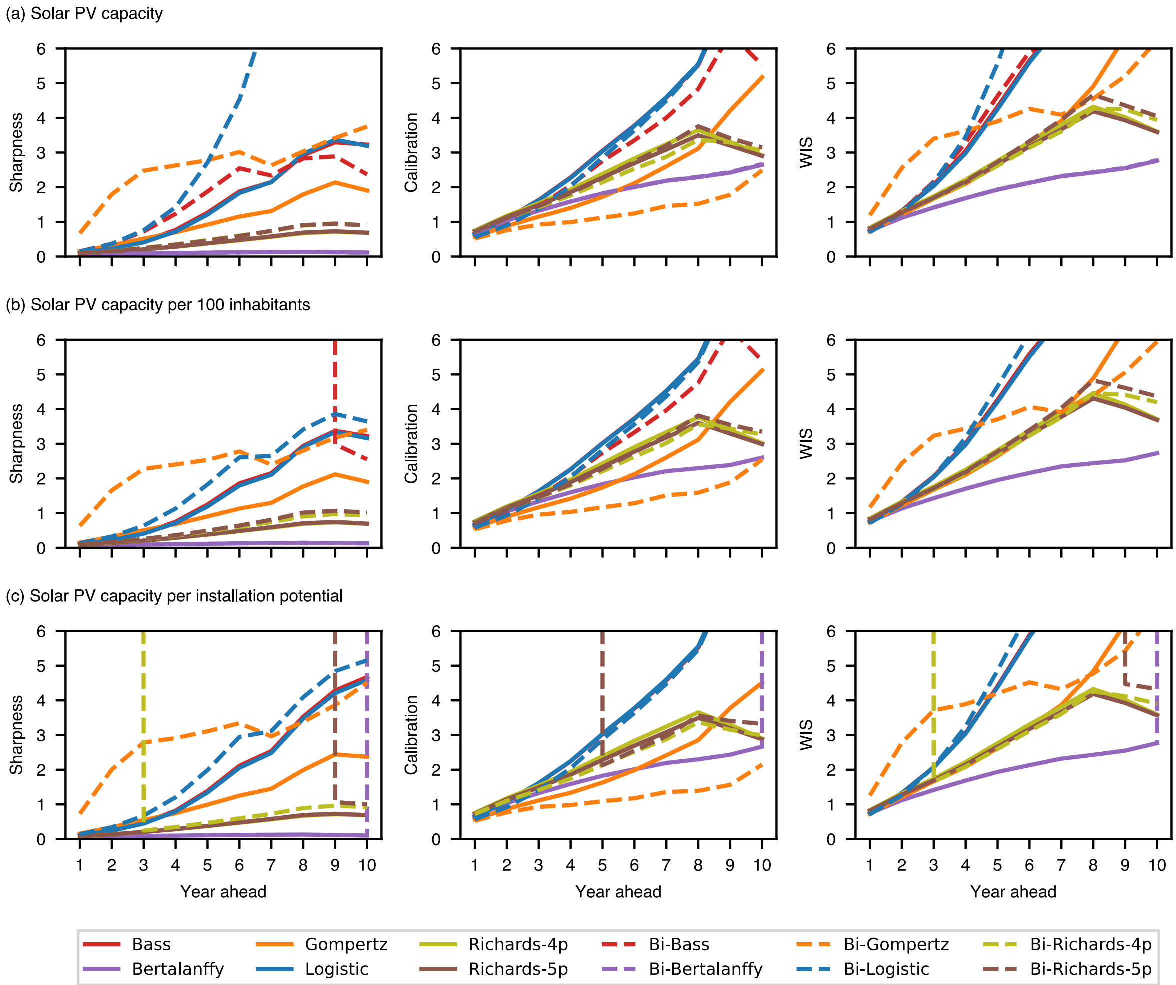

Figure 5-10. Temporal evolution of mean sharpness, calibration and Weighted Interval Score (WIS) for the probabilistic projections of solar PV capacities across Swiss municipalities and iterations of hindcasting. Scores can lay outside the plot boundaries in certain years.

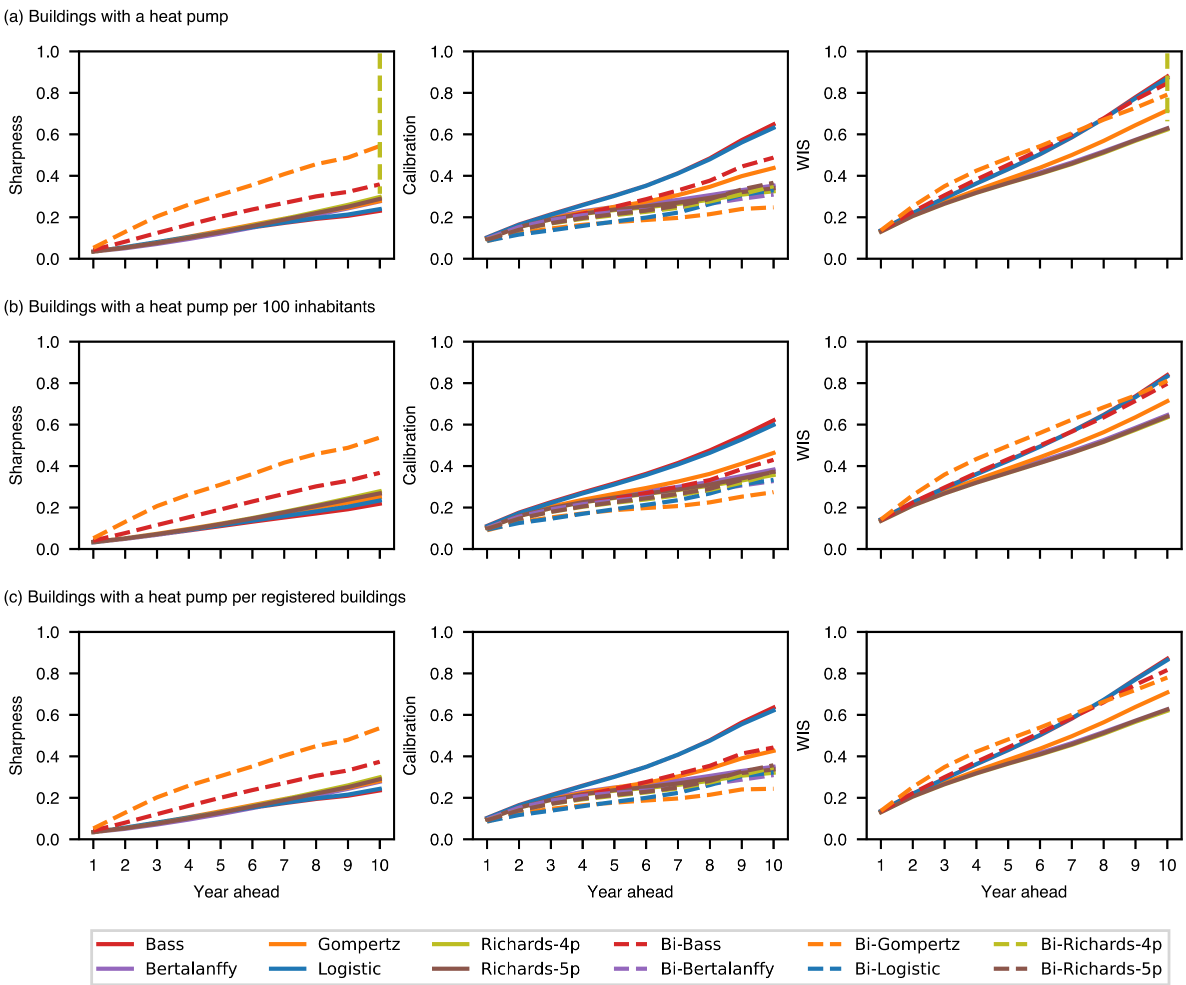

Figure 5-11. Temporal evolution of mean sharpness, calibration and Weighted Interval Score (WIS) for the probabilistic projections of buildings with a heat pump across Swiss municipalities and iterations of hindcasting. Scores can lay outside the plot boundaries in certain years.

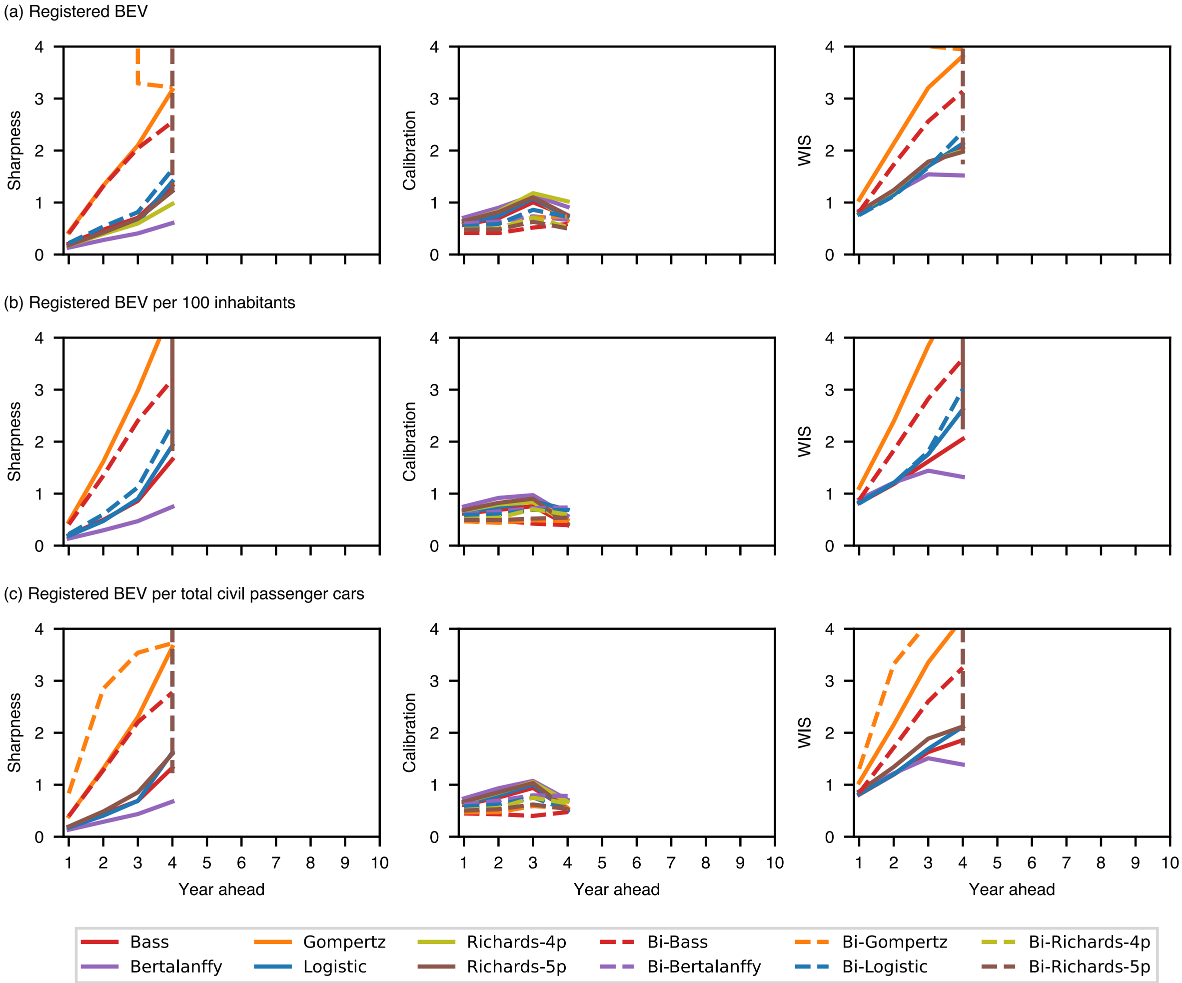

Figure 5-12. Temporal evolution of mean sharpness, calibration and Weighted Interval Score (WIS) for the probabilistic projections of Battery Electric Vehicles (BEV) across Swiss municipalities and iterations of hindcasting. Scores can lay outside the plot boundaries in certain years.

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5.2 Appendices of chapter 4

5.2.1 Appendix C

Table 5-2. Multicollinearity examination via variance inflation factors (VIF) for the stepwise regressions without cantons as dummy variables. A VIF of five or below indicates an acceptable moderate correlation. The response variables are logarithmically transformed and the predictive variables are standardised beforehand, except for the Energy City label which has binary values.

BUIL		INH	
Determinants	**VIF**	**Determinants**	**VIF**
Agricultural area	1.695	Population density	1.449
Detached houses	1.380	Detached houses	1.218
Unemployment rate	1.412	Unemployment rate	1.255
Unproductive area	1.588	Agricultural area	1.273
Average electricity price	1.250	Owned dwellings	1.603
Total dependency ratio	1.097	Energy City	1.102
Owned dwellings	1.741	Average net income	1.228
Average household size	1.603	Tertiary degree holder	1.714
Green voters	1.704	Average electricity price	1.054
Average net income	1.100		
Historical buildings	1.721		

Table 5-3. Multicollinearity examination via variance inflation factors (VIF) for the stepwise regressions with cantons as dummy variables. A VIF of five or below indicates an acceptable moderate correlation. The response variables are logarithmically transformed and the predictive variables are standardised beforehand, except for the Energy City label which has binary values.

BUIL		**INH**	
Determinants	**VIF**	**Determinants**	**VIF**
Agricultural area	2.185	Population density	1.651
Detached houses	1.542	Detached houses	1.352
Unemployment rate	3.823	Unemployment rate	2.553
Canton of Aargau	1.585	*Canton of Fribourg*	1.164
Unproductive area	1.798	*Canton of Aargau*	1.310
Canton of Fribourg	1.611	Agricultural area	2.122
Canton of Zurich	1.224	Energy City	1.158
Historical buildings	2.995	*Canton of Schwyz*	1.181
Average household size	1.790	*Canton of Appenzell Ausserrhoden*	1.052
Green voters	3.306	*Canton of Uri*	1.125
Canton of Appenzell Ausserrhoden	1.178	*Canton of Ticino*	1.494
Canton of Schwyz	1.294	*Canton of Zurich*	1.178
Total dependency rate	1.183	*Canton of Jura*	1.466
Average net income	1.231	*Canton of Valais*	1.550
Canton of Geneva	2.557	*Canton of Schaffhausen*	1.062
Canton of Basel-Stadt	1.040	Average net income	1.244
Canton of Neuchâtel	1.218	Tertiary degree holder	1.811
Canton of Vaud	4.274	*Canton of Graubünden*	1.445
CO_2 Act referendum	2.653	*Canton of Solothurn*	1.165
Canton of Schaffhausen	1.053	Total dependency ratio	1.152
Population density	1.841	*Canton of Lucerne*	1.187
		Canton of Glarus	1.013
		Canton of Geneva	1.380

5.2.2 Appendix D

Table 5-4. Results of ANOVA tests comparing respectively hot spots and cold spots to other municipalities of every Swiss canton with more than 30 municipalities. Note that hot and cold spots only include municipalities with a confidence level of at least 95%. Determinants that are only available at the cantonal level are removed, namely homeownership, unemployment rate and share of historical buildings. Some cantons have only one of the two indicators that has statistically significant results for both hot and cold spots (e.g. Lucerne, Fribourg, Ticino and Jura). Whereas some other cantons do not have any indicator that has statistically significant results for both hot and cold spots (e.g. Schwyz, Solothurn, St. Gallen, Thurgau and Geneva).

Table 5-4-1. Zurich

	Unit	**BUIL**			**INH**		
		Hot spots	Other	Cold spots	Hot spots	Other	Cold spots
Municipalities	–	45	78	39	25	114	23
Indicators							
BUIL	HP[a]/1'000 buil.	66.73***	274.59	–82.35***	87.53***	274.75	–105.34***
INH	HP/1'000 inh.	29.12***	59.29	–26.11***	42.12***	59.71	–36.04***
Sociodemographic determinants							
Agricultural area	%	5.8*	42.9	–4.6	6.5	44.7	–16.2***
Average household size	inh./household	0.05*	2.31	–0.05*	0.09***	2.31	–0.07**
Average net income	CHF/capita	–563	44'073	12'679**	–118	45'857	7'960
CO_2 Act referendum	%	–3.7*	44.2	7.3***	–3.2	44.7	4.5*
Green voters	%	–2.5	39.1	3.0	–2.4	39.4	0.6
Population density	inh./km^2	–341.0**	723.9	833.1***	–417.3***	723.5	1'202.2***
Total dependency ratio	–	0.60	65.60	1.32	2.27	65.90	–1.16
Unproductive area	%	0.2	2.3	0.7	–0.3	2.6	–0.0
Tertiary degree holder	%	0.1	34.1	7.5***	–0.8	35.8	1.9
Technoeconomic determinants							
Average electricity price	Rp./kWh	–0.08	17.49	0.56*	–0.36	17.62	0.27
Housing characteristics							
Detached houses	%	4.5*	61.0	–6.1**	7.8***	61.1	–10.5***

*Statistical significance codes: *** p ≤ 0.001, ** p ≤ 0.01, * p ≤ 0.5.*
[a] *HP stands for number of buildings heated by heat pumps.*

Table 5-4-2. Bern

	Unit	BUIL			INH		
		Hot spots	Other	Cold spots	Hot spots	Other	Cold spots
Municipalities	–	104	169	65	93	212	33
Indicators							
BUIL	HP[a]/1'000 buil.	75.28***	164.85	–45.18***	72.64***	162.86	–36.08*
INH	HP/1'000 inh.	24.25***	45.33	–4.47	22.61***	46.87	–11.90***
Sociodemographic determinants							
Agricultural area	%	2.5	51.4	–10.6***	3.5	48.7	5.1*
Average household size	inh./household	0.01	2.22	–0.07*	0.02	2.20	0.04
Average net income	CHF/capita	2'932**	33'172	–3'049*	2'522*	33'251	–4'673**
CO_2 Act referendum	%	2.8	36.2	–5.2**	2.5	35.8	–3.6
Green voters	%	2.7	31.5	–3.2	3.0	31.2	–3.0
Population density	inh./km^2	44.1	329.8	–224.6***	95.2	289.7	–161.0***
Total dependency ratio	–	–2.14	72.38	0.73	–1.93	72.18	2.20
Unproductive area	%	–1.4	4.0	5.9**	–3.9***	6.3	–5.0***
Tertiary degree holder	%	–0.5	29.9	–6.1***	–1.3	29.1	–1.1
Technoeconomic determinants							
Average electricity price	Rp./kWh	0.04	24.39	0.42	0.20	24.40	0.31
Housing characteristics							
Detached houses	%	10.2***	48.0	–4.8*	11.1***	47.9	–7.4*

*Statistical significance codes: *** $p \leq 0.001$, ** $p \leq 0.01$, * $p \leq 0.5$.*
[a] *HP stands for number of buildings heated by heat pumps.*

Table 5-4-3. Lucerne

	Unit	BUIL		
		Hot spots	Other	Cold spots
Municipalities	–	19	55	6
Indicators				
BUIL	HP[a]/1’000 buil.	109.27***	278.08	–125.04**
INH	HP/1’000 inh.	18.59**	57.98	–12.48
Sociodemographic determinants				
Agricultural area	%	7.0	56.4	–7.9
Average household size	inh./household	0.06	2.38	0.07
Average net income	CHF/capita	2’346	38’036	–13’911*
CO_2 Act referendum	%	4.4	40.0	–16.1***
Green voters	%	0.4	23.9	–17.0***
Population density	inh./km^2	–36.9	444.1	–396.1
Total dependency ratio	–	–1.26	63.73	6.58*
Unproductive area	%	–0.5	1.6	2.1
Tertiary degree holder	%	3.9***	27.3	–5.7***
Technoeconomic determinants				
Average electricity price	Rp./kWh	–0.45**	18.19	0.50
Housing characteristics				
Detached houses	%	2.4	50.0	–16.8***

*Statistical significance codes: *** p ≤ 0.001, ** p ≤ 0.01, * p ≤ 0.5.*
[a] *HP stands for number of buildings heated by heat pumps.*

Table 5-4-4. Fribourg

	Unit	INH		
		Hot spots	Other	Cold spots
Municipalities	–	2	116	8
Indicators				
BUIL	HP[a]/1'000 buil.	19.65	359.95	–113.25**
INH	HP/1'000 inh.	39.51	98.80	–54.15**
Sociodemographic determinants				
Agricultural area	%	–0.6	62.7	–22.8***
Average household size	inh./household	–0.16***	2.42	–0.02
Average net income	CHF/capita	–1'520	37'135	–2'490
CO_2 Act referendum	%	–11.6	37.5	16.0***
Green voters	%	–11.5	37.1	14.8***
Population density	inh./km^2	–43.7	218.4	1'058.9
Total dependency ratio	–	–2.12	63.40	–1.85
Unproductive area	%	–0.9	1.9	1.3
Tertiary degree holder	%	–2.9***	29.6	7.6***
Technoeconomic determinants				
Average electricity price	Rp./kWh	0.32	21.78	0.32
Housing characteristics				
Detached houses	%	2.9	63.2	–8.7

*Statistical significance codes: *** p ≤ 0.001, ** p ≤ 0.01, * p ≤ 0.5.*
[a] *HP stands for number of buildings heated by heat pumps.*

Table 5-4-5. Basel-Landschaft

	Unit	BUIL			INH		
		Hot spots	Other	Cold spots	Hot spots	Other	Cold spots
Municipalities	–	35	35	16	22	49	15
Indicators							
BUIL	HP[a]/1'000 buil.	14.18	256.29	–154.51***	13.86	256.30	–152.06***
INH	HP/1'000 inh.	–1.24	86.57	–62.53***	–4.62	86.38	–61.69***
Sociodemographic determinants							
Agricultural area	%	8.0*	40.3	–10.4*	1.7	43.5	–13.9**
Average household size	inh./household	0.05	2.27	–0.10*	0.04	2.28	–0.09*
Average net income	CHF/capita	–2'557	40'453	8'290*	–1'321	39'653	9'397*
CO_2 Act referendum	%	0.5	37.1	13.3***	0.9	37.1	13.7***
Green voters	%	5.4*	42.3	5.5*	4.9*	43.5	4.4
Population density	inh./km^2	–30.0	317.5	1'454.5***	3.9	306.0	1'542.0***
Total dependency ratio	–	–0.12	69.86	5.83	–0.65	70.02	5.96*
Unproductive area	%	–0.2	0.5	2.8	–0.4	0.8	1.5
Tertiary degree holder	%	1.4**	27.8	8.1***	0.9*	28.0	8.1***
Technoeconomic determinants							
Average electricity price	Rp./kWh	–1.25**	21.51	–1.05*	–0.88**	21.15	–0.68*
Housing characteristics							
Detached houses	%	–5.2	72.4	–4.3	–3.1	70.5	–1.5

*Statistical significance codes: *** $p \leq 0.001$, ** $p \leq 0.01$, * $p \leq 0.5$.*
[a] *HP stands for number of buildings heated by heat pumps.*

Table 5-4-6. Graubünden

	Unit	BUIL			INH		
		Hot spots	Other	Cold spots	Hot spots	Other	Cold spots
Municipalities	–	44	32	25	42	36	23
Indicators							
BUIL	HP[a]/1'000 buil.	88.58***	152.82	–64.79***	59.82*	167.85	–76.24***
INH	HP/1'000 inh.	15.83	78.68	–39.94***	33.58***	68.49	–29.70***
Sociodemographic determinants							
Agricultural area	%	–0.8	33.7	–17.6***	–0.5	33.1	–17.0***
Average household size	inh./household	0.06	2.15	–0.14**	0.00	2.18	–0.17***
Average net income	CHF/capita	–183	33'042	11'513*	–1'349	33'661	11'907*
CO_2 Act referendum	%	3.7	40.5	1.5	2.0	41.6	0.2
Green voters	%	5.1*	23.6	2.5	1.3	25.8	0.1
Population density	inh./km^2	74.7**	28.1	0.5	26.1	55.6	–25.2
Total dependency ratio	–	–1.43	73.33	–5.43	3.65	70.62	–3.43
Unproductive area	%	–18.0	34.9	6.7	–9.7	30.6	9.4
Tertiary degree holder	%	1.7	23.6	1.7	–0.9	25.1	0.1
Technoeconomic determinants							
Average electricity price	Rp./kWh	–1.36	21.38	–0.26	–2.38	21.74	–0.08
Housing characteristics							
Detached houses	%	3.2	50.5	1.0	0.5	52.6	–2.9

*Statistical significance codes: *** p ≤ 0.001, ** p ≤ 0.01, * p ≤ 0.5.*
[a] *HP stands for number of buildings heated by heat pumps.*

Table 5-4-7. Aargau

	Unit	BUIL			INH		
		Hot spots	Other	Cold spots	Hot spots	Other	Cold spots
Municipalities	–	47	93	60	27	121	52
Indicators							
BUIL	HP[a]/1'000 buil.	99.62***	282.51	–38.79*	86.29***	296.69	–54.03**
INH	HP/1'000 inh.	24.91***	75.94	–16.52**	23.54***	79.04	–21.64***
Sociodemographic determinants							
Agricultural area	%	12.6***	42.6	–6.6**	4.3	45.6	–9.9***
Average household size	inh./household	0.06*	2.29	0.01	0.01	2.30	0.01
Average net income	CHF/capita	2'085	38'778	2'796	–629	39'262	3'577
CO_2 Act referendum	%	0.3	37.4	4.2*	0.0	37.2	6.0***
Green voters	%	–3.6*	33.8	0.6	–2.0	32.5	3.1
Population density	inh./km^2	–228.8***	564.1	100.0	–198.9**	504.1	242.7**
Total dependency ratio	–	–3.37*	64.31	0.69	–2.30	63.99	0.18
Unproductive area	%	1.0	1.7	0.9	0.4	2.0	0.4
Tertiary degree holder	%	–0.7	29.8	2.4**	–0.2	29.4	3.6***
Technoeconomic determinants							
Average electricity price	Rp./kWh	–1.16**	19.02	0.09	0.27	18.62	0.47
Housing characteristics							
Detached houses	%	–1.8	68.8	–1.7	–1.3	68.2	–0.9

*Statistical significance codes: *** p ≤ 0.001, ** p ≤ 0.01, * p ≤ 0.5.*
[a] *HP stands for number of buildings heated by heat pumps.*

Table 5-4-8. Ticino

	Unit	INH		
		Hot spots	Other	Cold spots
Municipalities	–	17	89	2
Indicators				
BUIL	HP[a]/1'000 buil.	19.44	138.45	74.64****
INH	HP/1'000 inh.	36.28	58.19	20.88
Sociodemographic determinants				
Agricultural area	%	–5.3*	12.5	–7.3
Average household size	inh./household	–0.14*	2.13	0.03
Average net income	CHF/capita	–2'224	38'819	–1'513
CO_2 Act referendum	%	3.7	41.7	0.8
Green voters	%	6.1**	25.8	6.6
Population density	inh./km^2	–42.5	691.7	–460.6
Total dependency ratio	–	10.23***	70.19	–7.71
Unproductive area	%	–1.1	10.8	–5.8*
Tertiary degree holder	%	–2.4**	31.8	5.1***
Technoeconomic determinants				
Average electricity price	Rp./kWh	2.33***	22.20	–1.06***
Housing characteristics				
Detached houses	%	–2.5	68.1	–4.2

*Statistical significance codes: *** p ≤ 0.001, ** p ≤ 0.01, * p ≤ 0.5.*
[a] *HP stands for number of buildings heated by heat pumps.*

Table 5-4-9. Vaud

	Unit	BUIL			INH		
		Hot spots	Other	Cold spots	Hot spots	Other	Cold spots
Municipalities	–	29	258	13	67	115	118
Indicators							
BUIL	HP[a]/1'000 buil.	102.82***	138.83	–82.85***	47.34***	144.36	–24.79*
INH	HP/1'000 inh.	28.48***	36.35	–24.47***	14.70**	39.72	–12.60***
Sociodemographic determinants							
Agricultural area	%	3.3	54.9	–13.0*	5.9	54.6	–3.1
Average household size	inh./household	0.13**	2.39	–0.18**	0.04	2.40	–0.05
Average net income	CHF/capita	18'533	42'845	7'177	7'484	40'707	6'533
CO_2 Act referendum	%	8.2***	44.0	8.5**	2.9	42.0	6.3***
Green voters	%	–0.6	44.2	1.7	–0.3	42.7	3.9***
Population density	inh./km^2	95.5	402.9	1'030.3	116.1	190.5	611.1***
Total dependency ratio	–	1.92	66.73	–2.08	2.11	67.38	–2.62*
Unproductive area	%	–0.2	1.3	0.7	–0.7	1.7	–0.4
Tertiary degree holder	%	6.3*	34.9	5.6**	–0.6	34.5	3.5**
Technoeconomic determinants							
Average electricity price	Rp./kWh	0.10	21.31	–0.34***	–0.12	21.31	0.01
Housing characteristics							
Detached houses	%	10.1***	57.1	–8.9*	3.5	57.9	–2.6

*Statistical significance codes: *** $p \leq 0.001$, ** $p \leq 0.01$, * $p \leq 0.5$.*
[a] *HP stands for number of buildings heated by heat pumps.*

Table 5-4-10. Valais

	Unit	BUIL			INH		
		Hot spots	Other	Cold spots	Hot spots	Other	Cold spots
Municipalities	–	29	88	5	27	64	31
Indicators							
BUIL	HP[a]/1'000 buil.	130.93***	114.66	–44.94	95.52***	130.84	–31.61
INH	HP/1'000 inh.	33.05***	52.98	–23.52	36.26***	56.16	–16.98**
Sociodemographic determinants							
Agricultural area	%	5.4*	20.4	–10.0	5.1	21.6	–5.6*
Average household size	inh./household	0.05	2.17	–0.02	–0.01	2.18	0.00
Average net income	CHF/capita	–1'212	33'511	–5'087	1'411	32'715	–49
CO_2 Act referendum	%	–1.6	36.8	–7.4	–1.9	36.9	–1.3
Green voters	%	12.6***	18.4	–9.0	9.1***	21.7	–10.8***
Population density	inh./km^2	169.1**	98.4	–61.4*	122.8	119.0	–39.8
Total dependency ratio	–	–1.30	68.75	–7.64	3.22	68.54	–4.42
Unproductive area	%	–18.1***	40.0	20.2	–9.9	36.5	8.6
Tertiary degree holder	%	5.8***	21.3	1.0	8.0***	20.5	2.0
Technoeconomic determinants							
Average electricity price	Rp./kWh	1.00*	18.32	1.04	–0.40	19.08	–1.53*
Housing characteristics							
Detached houses	%	11.7***	56.7	–18.5	9.9***	59.5	–11.8**

*Statistical significance codes: *** p ≤ 0.001, ** p ≤ 0.01, * p ≤ 0.5.*
[a] *HP stands for number of buildings heated by heat pumps.*

Table 5-4-11. Jura

	Unit	INH		
		Hot spots	Other	Cold spots
Municipalities	–	4	45	4
Indicators				
BUIL	HP[a]/1’000 buil.	75.36	170.15	–53.30
INH	HP/1’000 inh.	22.92	62.75	–25.73
Sociodemographic determinants				
Agricultural area	%	–3.6	50.7	4.8
Average household size	inh./household	0.00	2.25	0.11
Average net income	CHF/capita	630	31’420	9’048
CO_2 Act referendum	%	4.0	36.9	–0.8
Green voters	%	2.6	46.7	2.4
Population density	inh./km^2	96.2	84.1	–44.2
Total dependency ratio	–	1.49	75.69	–7.37
Unproductive area	%	–0.5	0.9	–0.2
Tertiary degree holder	%	–1.0***	24.4	–0.2
Technoeconomic determinants				
Average electricity price	Rp./kWh	0.18	25.53	0.06
Housing characteristics				
Detached houses	%	4.1	67.6	–14.5*

*Statistical significance codes: *** $p \leq 0.001$, ** $p \leq 0.01$, * $p \leq 0.5$.*
[a] *HP stands for number of buildings heated by heat pumps.*